IMPROVING INDUSTRIAL NETWORKS THROUGH BIOLOGICALLY-INSPIRED URBAN-INDUSTRIAL ECOSYSTEMS

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Zackery B. Morris

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IMPROVING INDUSTRIAL NETWORKS THROUGH BIOLOGICALLY-INSPIRED URBAN-INDUSTRIAL ECOSYSTEMS

Approved by:

Dr. Bert Bras, Advisor
School of Mechanical Engineering
Georgia Institute of Technology

Dr. Marc Weissburg
School of Biological Sciences
Georgia Institute of Technology

Dr. John Crittenden
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Julie Linsey
School of Mechanical Engineering
Georgia Institute of Technology

Dr. Kate Fu
School of Mechanical Engineering
Georgia Institute of Technology

Dr. Astrid Layton
School of Mechanical Engineering
Texas A&M University

Date Approved: [June 5, 2020]

In loving memory of my father, James Elijah Morris III

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LIST OF SYMBOLS AND ABBREVIATIONS

AMI	Average Mutual Information
ASC	Ascendency
DC	Development Capacity
DG	Design Guideline
EIP	Eco-Industrial Park
ENA	Ecological Network Analysis
FCI	Finn Cycling Index
MFA	Material Flow Analysis
MPL	Mean Path Length
SCC	Strongly Connected Component
StDev	Standard Deviation
UIE	Urban-Industrial Ecosystem
UM	Urban Metabolism

SUMMARY

Biologically-Inspired Design is a growing field that has many applications. While this is normally used for individual products or materials, applied at a systems level, the inspiration can stem from the structure and makeup of ecosystems. Over the last few decades, ecologists have developed Ecological Network Analysis (ENA) to better understand ecosystems, and both industrial and urban systems have been analyzed using ENA. The industrial and urban systems can be represented in a similar fashion to natural ecosystems in that they are a network of connections with producers (prey) and consumers (predators). Specifically, Eco-Industrial Parks (EIPs) that look to mimic the cyclic nature of food webs have been analyzed using ENA showing that these networks can still be improved significantly before they reach the levels of observed natural food webs. Similarly, urban networks (such as water and energy networks) have been looked at with ENA at a high level with insight gained about trophic levels in a city and how they compare with food webs. However, the industrial and urban networks have been analyzed at different scales and in separate systems. Applying ENA to these networks is still in its infancy, and as such, there is a great potential to further the analysis to include a greater number of metrics that have not been applied previously. These metrics include identifying critical actors in a network and calculating the overall network and individual actor utility within the system. Thus far, this has only been used to analyze existing networks, but the ENA method could be adapted into a way to design industrial and urban networks thus truly becoming Biologically-Inspired Design. The natural ecosystems exhibit a number of characteristics (such as a high degree of cycling and the inclusion of many detritus actors

that process waste) that when applied to industrial and urban networks, will likely increase the sustainability measured by reduced resource consumption and increased resiliency.

This dissertation furthers the use of ENA for industrial and urban networks. First, additional metrics from ENA are included in the analysis that have not previously been explored. In addition, more human created networks are added to create an even larger dataset of networks that have been analyzed with this method. This addition of new metrics and new networks give greater understanding into both ENA and the networks being analyzed. Finally, ecologically derived design principles are created and tested to increase sustainability for the human-designed systems.

This dissertation contributes in both understanding and a new method to plan and design networks. In applying the ENA method more robustly (using more metrics) and to more networks, there is a greater amount of insight gained into how the analysis can be applied to human-engineered systems. Also, there is greater knowledge about how these networks are currently structured which leads to better decision making for the present and future. This enhanced knowledge allows for a new way to design industrial and urban networks that is unique in its incorporation of ecological principles.

CHAPTER 1. INTRODUCTION

This chapter introduces the motivation, goals, and contributions of this work. In addition, it outlines the research tasks and plan that were originally put forth to guide this research. Each of these will addressed in the proceeding chapters, always pointing back to these fundamental contributions that are outlined.

1.1 Motivation

The industrial sector is extremely resource intensive. Industrial energy consumption is 22% of total energy consumption in the United States (US Energy Information Administration 2017), with irrigation, livestock, aquaculture, industrial and mining processes accounting for 42% of all water withdrawals (US Geological Survey 2010). In addition, raw material usage in the U.S. rose almost 3 times faster than population from 1910 to 2010 (Center for Sustainable Systems 2016). As such, there have been a number of efforts to curb industrial resource usage. The US Environmental Protection Agency created a program called E3 focusing on increasing sustainability of communities, manufacturers, and supply chains (US Environmental Protection Agency 2017). Many specific industries have also made this a goal such as automotive plants using landfill gas to power onsite energy and heat generation (BMW 2014). Beyond the individual industry level, there has also been a lot of work on industrial networks to move towards sustainability. This has led to the concepts such as industrial ecology (Frosch 1992) and industrial symbiosis (Earley 2015) where the goal is to understand these networks in a similar way to ecological systems and create symbiotic relationships between industries. Furthering this concept into practice led to the creation of Eco-Industrial Parks (EIPs) that looked to mimic the connectedness of natural ecosystems (Hardy and Graedel 2002).

Similar to industry, cities are a critical component of today's society. Currently, half of the world's population lives in cities, and this is expected to grow to 60% by the year 2030 (United Nations Habitat 2015). With this large concentration of population, cities are also very resource intensive. While only taking up 3% of the land area of the globe, cities consume 60-80% of the energy and produce 75% of the carbon emissions (United Nations Habitat 2015). In addition, the 27 megacities, defined as having a population of 10 million or more, consume 9% of all electricity, 10% of all gasoline, and generate 13% of all solid waste (Kennedy et al. 2015). This growth and resource usage puts a large stress on water supplies, the living environment, and human health. The United Nations has made it one of their sustainable development goals to "make cities inclusive, safe, resilient and sustainable," with other goals pertaining to clean water, clean energy, and combating climate change (United Nations 2015a). Urban infrastructure plays a critical role in cities, as it is what allows the city to function. This infrastructure is becoming increasingly vulnerable as climate changes and as populations grow. There is an obvious need to tackle the issue of growing cities, especially in regards to the infrastructure that supports them.

Cities in the US were typically built around the industries located there, but most of this industry has been pushed to the hinterlands in favor of services. However, industry is still very much tied to the sustainability of cities. There is enormous potential to make industry more efficient, benefitting both industry and the cities it is located within (Sall and Shah 2015). It has been recommended to increase the amount of industrial mixed-use districts and light industry within cities to increase economic and social viability (Cotter 2012). Efforts to increase city sustainability have seldom focused on industry, instead focusing on infrastructure and planning.

Kenworthy has proposed principles of an "eco-city" that revolve around urban form and transport (Kenworthy 2006). Dias et al suggests that there is a need to rethink urban design as a bottom up approach to create more sustainable cities (Dias, Curwell, and Bichard 2014). Others have proposed green urbanism (Anastasiadis and Metaxas 2013), green infrastructure (Ahern 2007; Tzoulas et al. 2007), and landscape ecology (Wu 2008), all of which look to better integrate the human and built environment with the living one. There are similarities between all of these approaches, but the variance shows there is still a lack of understanding about how cities function and how they can be improved. This dissertation looks to clarify this by treating cities and the industries contained within them as ecosystems and studying those through a lens of ecology. This chapter introduces the tasks of how that is accomplished as well as addressing the main goals and contributions of the work. This starts with the overall research question that looks to be answered.

1.2 Overall Research Question

Can biologically-inspired design, through the principles and metrics of ecology, be applied to urban-industrial systems to increase sustainability, measured by reduced resource consumption and increased resiliency?

1.3 Research Goals

1.3.1 Analyze urban-industrial networks using ecological principles and metrics

Ecological network analysis (ENA) allows ecologists to characterize food webs based on characteristics of performance related to the maturity and complexity of those networks (Ulanowicz 2004). This network analysis can be used for any type of network and has been used to analyze EIPs (Layton 2014). An objective of this dissertation is to analyze the urban-industrial networks using ENA. By doing so, a direct comparison is made to existing EIPs, other networks that have used this analysis, and natural food webs. This is the basis for the biological inspiration, as it provides metrics with which to compare between human created and ecological networks. These systems analyzed are models that represent the interactions between the various components. The systems look at water, energy, food, materials, and various combinations of these resources. Some of these systems are from literature while others are generated for the purpose of analysis and testing.

1.3.2 Understand and improve resiliency of urban-industrial systems

Greater effort is being put into creating resilient systems and is becoming ever more important as the climate changes. This has prompted initiatives such as the 100 Resilient Cities, founded by the Rockefeller Foundation (100 Resilient Cities 2017). This dissertation looks to add to the understanding of the resilience of urban-industrial systems through the analysis conducted. That resilience is directly tied to the sources of critical resources and how those resources are processed in the system, especially as waste streams. It is also tied to the interactions between all actors in the system. By more clearing understanding those sources and interactions, the goal is to propose ways to increase resilience of these systems. This comes in the way of creating more thoroughly connected networks that treat the network as a true system instead of individual components that share central infrastructure. This dissertation aims to explore this concept to understand how these systems can best be integrated for greater resilience.

1.3.3 Determine critical actors in urban-industrial systems and their functional roles

A key to sustainable and resilient systems is identifying the critical actors that are crucial to network operation. This could include a power plant that is vulnerable because it is the only energy source in a network, or the supply of a specific component in an assembly line that would halt production if not supplied on time. Natural ecosystems are heavily reliant on decomposer actors to process waste and return nutrients and energy to the system. They are also reliant on primary producers to process those nutrients into something useful and to bring in energy from the sun. These roles are found in almost all natural ecosystems, and these systems could not function without them. For human-designed systems, it is unclear if these roles exist, or if there are other critical roles that are present within all of these systems. This dissertation will identify the critical actors and their functions in urban-industrial systems.

1.4 Fundamental Contributions

This dissertation will further the idea of urban-industrial systems as ecosystems through quantifiable results. While this idea of these systems as ecosystem has been proposed through principles such as infrastructure ecology, it has not been quantified and tested. The hope of this dissertation is to provide that testing that has not been done before.

1.4.1 Addition of new ecological metrics for use in industrial network analysis

Previous industrial ecology research has used a limited number of ecological metrics to analyze industrial networks, mainly focused around the structure of these networks (Layton, Bras, and Weissburg 2016a, 2016b; Reap and Bras 2014). These metrics are focused on single values that are ascribed to the network and do not take into account all of the individual interactions that occur. While these metrics are useful, there are many additional ecological metrics that can be used to analyze these same networks, as well as new networks. The addition of more metrics provides a greater degree of depth to the analysis and may show patterns or trends that were not before known. This dissertation adds some of these more robust metrics. Those metrics include Centrality, Utility, Mixed

Trophic Impact, Control, and Dependence analysis. With Centrality, it has been shown that for the majority of ecosystem models, more than 80% of the system throughflow is concentrated through 20% of the nodes, with these nodes often being primary producers, dead organic matter, or bacteria (Borrett 2013). This metric allows the major actors to be identified, which has not been done before for urban-industrial systems. Utility analysis allows one to quantify the positive, negative, or neutral effect each actor has on each other actor (Fath 2007). This type of analysis provides insight into both individual actors and the network as to the types of relationships (positive, negative, or neutral) that exist, and it has never been done before on urban-industrial networks. These in combination with the other new forms of analysis provide a much wider range of knowledge about these systems that is completely novel.

1.4.2 Dataset of urban-industrial networks that have been analyzed through the lens of ecological metrics.

A robust set of networks that have been thoroughly examined and analyzed is needed. The dataset of urban-industrial systems presented in this dissertation builds upon previously analyzed systems by combing these all into one source. This allows for the comparison between networks as well as a more overall idea of how these systems operate and perform. Additionally, the dataset of Urban-Industrial Ecosystems contains a much greater wealth of data because of the presence of flow information. The flow information more than doubles the number of metrics that can be used to describe these systems and allows for further comparison to the natural systems.

1.4.3 Further testing and validation of the application of ecological metrics to human systems.

The use of ENA for human created systems is still in its infancy. There are only a handful of studies that have used this type of analysis and there are still a number of questions that revolve around the utility and validity of this analysis. These questions involve the scale at which this analysis is appropriate, the level of aggregation for actors in industrial and urban settings, and whether there is an idealized system that all networks should try to look like. This dissertation looks to further the knowledge of the usefulness of ENA when applied to human created systems. This will be done by thoroughly looking at many scenarios and configurations of industrial and city systems and learning more about how changes affect the ecological metrics. By documenting how the changes affect the metrics, this will provide insight into how the tool can be best used. Additionally, the analogy between human-designed and natural will be examined, highlighting the key differences as to where that analogy may breakdown or what may explain the gap in performance.

1.4.4 Design guidelines for sustainable Urban-Industrial Ecosystems

The culmination of the understanding gained is a series of design guidelines for Urban-Industrial Ecosystems to aid in the future creation of these systems. These guidelines look to increase the sustainability of these systems and better mimic the natural systems they are compared against. The design guidelines involve fully modeling the systems, increasing the use of recyclers, decreasing the reliance on single sources, and decreasing the level of aggregation. To create the best system possible, all resources and wastes need to be utilized fully. The future design of these systems will identify where there are current gaps in the resource utilization, allowing for those gaps to be filled by specific functional actors. These design guidelines are created specifically for these systems, but can be adapted to fit any human-designed system and increase sustainability.

1.5 Research Plan

To answer the fundamental question of this research and meet the research goals, the following plan is proposed. This plan looks to dive into cities, industry, and ecology. Through the understanding of each, the culmination will be to combine this knowledge to analyze city-industrial networks from an ecological perspective.

Research tasks (RT) are as follows:

RT1: Gather and analyze existing urban and industrial network studies

RT2: Determine new forms of ecological analysis from ENA to use in urban-industrial ecosystem analysis

RT3: Analyze existing networks with new analysis

RT4: Generate new and theoretical networks with enhanced analysis to understand ideal network design

1.5.1 RT1: Gather and analyze existing urban and industrial network studies

A lot of work has been done on both urban and industrial networks, specifically looking at their sustainability. One of these areas is Urban Metabolism, which looks at all of the flows into, around, and out of a city. While Urban Metabolism is not the main focus of this work, the data present in these studies and others like them can be used to understand how these networks are traditionally structured and analyzed. Some of these studies only provide the structure of the systems, while others provide the actual flows. These systems can be analyzed using ENA, and the results compared against one another and food webs.

1.5.2 RT2: Determine new forms of ecological analysis from ENA to use in urban-industrial ecosystem analysis

As stated earlier, ecologists have developed ENA to understand, characterize, and analyze ecological food web networks. Much of this work has led to the creation of metrics that can be calculated for any network. Previously, Layton has used a number of these metrics from ENA to analyze EIPs (Layton et al. 2016a). These metrics provide in-depth knowledge of the network structures and flows. However, this list of metrics ignores some of the other types of analysis that has been done by ecologists. Each of the different types of analysis or metrics looks at a different aspect of the network, but all may not be applicable to urban-industrial ecosystems. The most relevant pieces from ENA not previously looked at by Layton will be combined with those metrics from Layton to create a comprehensive list for analysis. Once this list is compiled, the new metrics will be incorporated into the existing ecological analysis tool. This will be done by including the calculations for the new metrics into the existing tool and making any modifications that need to be made such as new data structures that need to be added for the new metrics.

1.5.3 RT3: Analyze existing networks with new analysis

The new forms of analysis from RT2 will be adapted into a toolkit for networks analysis that will include the previously used metrics. This updated toolkit will be used to analyze previously compiled networks which includes the networks from RT1 and those previously analyzed by Layton (Layton et al. 2016a). The new metrics will give a greater amount of insight into the networks. Previously, the EIPs analyzed were ranked based on performance. These new metrics may reinforce those rankings or may show that the rankings should be adjusted. In addition, these new networks that have not been analyzed can be added to this dataset and compared to all other networks.

1.5.4 RT4: Generate new and theoretical networks with enhanced analysis to understand ideal network design

Using the understanding gained from the analysis of existing networks, this will allow new networks to be designed, going beyond analysis. These theoretical systems will have a real-world basis but go beyond what is currently in practice to further the ideas of bio-inspired systems design, including the addition of new technology. These newly designed networks will incorporate existing industrial networks with data gathered about surrounding urban areas. This will allow new ideas and connections to be tested to move towards an ideal system that acts most similar to a natural ecosystem. They will be optimized to maximize the ecological metrics, but also analyzed from a traditional sustainability perspective to understand this trade off. The ideal networks will take the best elements of the existing networks and combine them together.

1.6 Dissertation Outline

Following this introduction chapter, there are two chapters of background information, followed by four chapters of analysis and discussion, and a final conclusion chapter. The first background chapter, Chapter 2, is a literature review covering topics of sustainable and resilient design, the use of ecology in urban and industrial systems, and a brief introduction into ENA. Chapter 3 thoroughly outlines ENA, providing definitions and formulas for the metrics that are used in the analysis chapters. In addition, it provides a critical look at the analogy between natural and human systems and the limitations of this analogy and analysis. This leads into Chapter 4 which analyzes the dataset of Urban-Industrial Ecosystems using ENA with a comparison to natural and human-designed systems. Additionally, this includes an analysis based on network type and actor inclusion. Chapter 5 introduces additional ENA metrics that primarily focus on identifying the key actors within these systems. These metrics are used to analyze the natural and human-made systems. Chapter 6 proposes four design guidelines for urban-industrial systems to increase sustainability and resilience. These guidelines are based upon quantitative (correlation results) and qualitative analysis presented in this chapter. The last analysis chapter, Chapter 7, tests these design guidelines by modifying different human-designed systems to understand the effects on ecological performance and sustainability. Finally, Chapter 8 provides a summary, while proposing future work to be done.

CHAPTER 2. LITERATURE REVIEW

This chapter summarizes literature relevant to sustainable systems, bio-inspired design, industrial and urban network analysis, and ecosystem analysis. This review provides the main motivation and backbone of this dissertation by showing the current methods and ideas available surrounding Urban-Industrial Ecosystems, while identifying some of the flaws in the previous analysis and providing a solution in the form of Ecological Network Analysis. It is shown how Ecological Network Analysis has been applied to these systems previously and how that can be furthered to move from analysis to design.

2.1 Sustainable and Resilient Systems

Sustainability is a broad term with many definitions, with many focused around sustainable development. One of the most well-known definitions comes from the Brundtland Report that states “sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (World Commission on Environment and Development 1987). Stemming from this in 2015, the United Nations adopted 17 Sustainable Development Goals focused around people, planet, prosperity, peace, and partnership (United Nations 2015b). These goals are wide ranging, but specifically mention industry, cities, production, energy, and water. Sustainability, in general, is the ability to exist through all situations and therefore can be closely tied to resilience (Fiksel 2003). Resilience is the ability to resist disorder, but there are multiple types of resilience. Engineering resilience can be defined as how quickly a system returns to steady state after a disturbance. Ecological resilience can be defined by the magnitude of a disturbance a system can endure without leading to system reconstruction (Gunderson and Pritchard 2002). Both of these take into account different aspects of resilience, but do not fully capture the term. It has been proposed that there are four Rs of resilience with those four being robustness, redundancy, resourcefulness, and rapidity (Bruneau et al. 2003; Bruneau and Reinhorn 2007).

Resilience speaks to systems dynamics as it is a combination of the complex interactions that occur. Typically, however, systems are not designed with resilience in mind. Most engineered systems are designed in a hierarchical fashion with the overall system function being designed first followed by all the subsystems to accomplish that function leading to potentially rigid and brittle designs (Fiksel 2003). Instead, these centralized systems could be replaced with decentralized ones that accomplish the same goals with more redundancy built in to combat that rigidity. Fiksel proposes sustainable systems exhibit four characteristics: diversity, efficiency, adaptability, and cohesion. In this way, the function is not the main design goal, but rather how all of the components work together to accomplish that function (Fiksel 2003).

2.2 Biologically Inspired Design

Biologically inspired design is simply defined as looking to some part of nature for a novel solution to an engineering problem (French 1994). This inspiration can fall into a number of categories including form, architecture, surface, material, function, process, and system (Nagel, Schmidt, and Born 2018). While not an exhaustive list, it is clear there are many applications for this type of design. Additionally, methods have been developed to evaluate the analogies that are created between engineered solutions and nature (Helms and Goel 2014). Bio-inspired design at the process level has been used to aid in the manufacturing of transmission cases (Park and Tran 2013), manufacturing systems (Leitão, Barbosa, and Trentesaux 2012; Tang et al. 2009), and supply chain management (Fan et al. 2014). It has also been used to mimic function in the form of copying shark skin to improve aerodynamics (Richard 2009), designing auto parts like bones to reduce weight (Orf 2013), and copying insect neurons to create a better collision detection for vehicles (Stafford, Santer, and Rind 2007). There is much to be learned from these many examples, but the main focus of the bio-inspiration in this dissertation is at the system level. Specifically, this means drawing inspiration from and mimicking the structure of natural ecosystems.

2.2.1 Application of Ecology in Industry

The application of ecology in industry is a relatively new idea. This idea was started by Frosch in 1992 with the introduction of industrial ecology (Frosch 1992). The field of industrial ecology is one that draws an analogy between industrial networks and ecological ones by relating industrial processes to organisms. Through this analogy, the hope is to minimize wastes by including more cyclical practices in these industrial networks (Frosch

1992). This is similar to the concept of industrial symbiosis which is collocating industries in able to more freely exchange resources and by products to gain competitive advantage (Chertow 2004). The implementation of industrial ecology and symbiosis looks like industrial ecosystems in the form of eco-industrial parks (EIPs), many of which have been proposed or created. These EIPs look to mimic natural food web structure and form, and not only that they can be mimicked, but also that there is “an analogous relation between biological and industrial food webs, and tools for evaluating the former are valid for the latter” (Hardy and Graedel 2002). One of the most famous EIPs is the Kalunborg Symbiosis located in Denmark shown in Figure 1. This network was analyzed using different network analysis techniques to understand it’s resilience. This showed the power plant being the most critical node in the network as it is the most central, and thus has the largest impact on the resilience. Overall, the resilience of this network has increased from 1960 to 2010 shown by a reduced vulnerability of the nodes, although it is suggested that adopting the diversity of natural ecosystems can better improve resilience (Chopra and Khanna 2014).

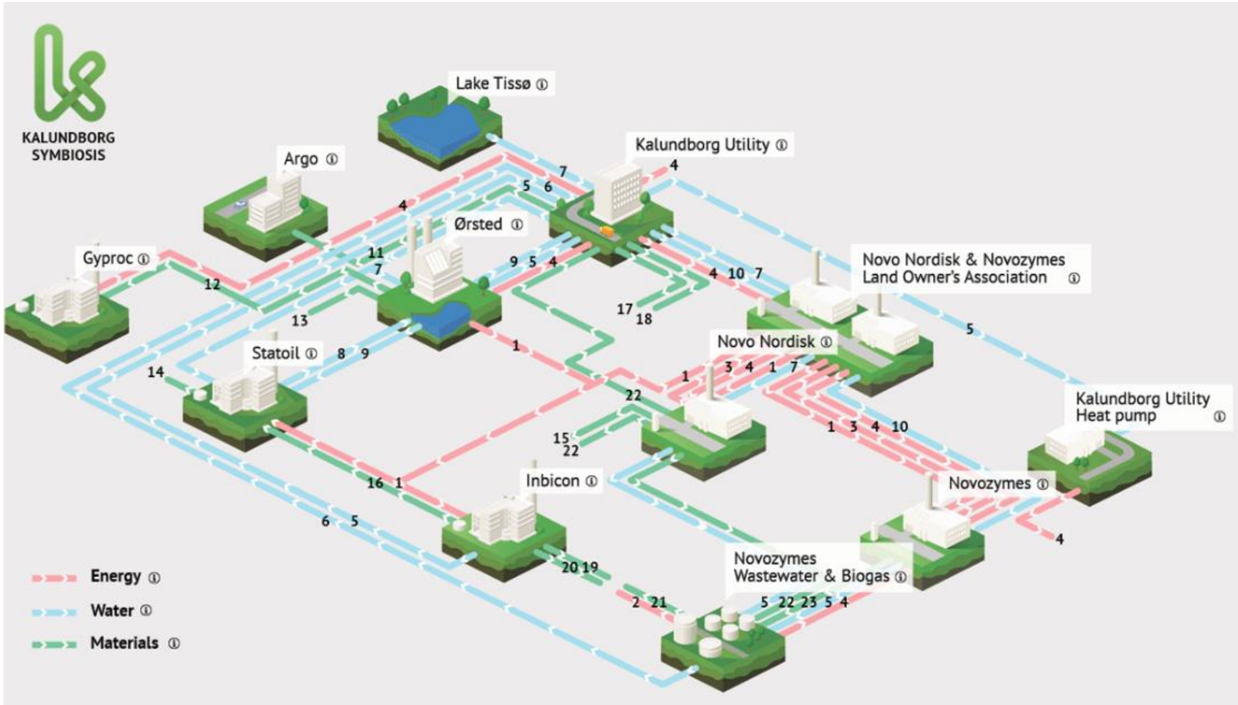


Figure 1 Kalunborg Symbiosis Eco-Industrial Park (Kalunborg n.d.)

2.2.2 Application of Ecology in Cities

In addition to the industrial applications of ecology, cities have often been analyzed in a similar light. One of the best examples of this is urban metabolism. Urban metabolism attempts to draw the parallel between cities and ecological processes by quantifying "the technical and socioeconomic processes that occur in cities, resulting in growth, production of energy, and elimination of waste" (Kennedy, Cuddihy, and Engel-Yan 2007). In this way, urban metabolism is an accounting method for what goes into and out of a city. However, a review of over 100 urban metabolism studies showed there is a large variance in how these studies are done, and there is still room for improvement in this method, with one of the main challenges being "how to model the system's network" and realize "its effects on the environment" (Beloin-Saint-Pierre et al. 2015). Also, urban metabolism has been criticized for modeling cities as organisms rather than ecosystems, which hinders the view of the city as a network and reduces it down to a single entity (Golubiewski 2012). A review of other ecological approaches in planning cities found that there is "a need for developing an accurate and comprehensive micro-level urban ecosystem sustainability assessment method that also have the capability to be integrated with larger scale assessment tools" (Yigitcanlar and Dizdaroglu 2015).

Xu et al states that "analogies to ecological systems may reveal new ways to analyze urban systems and provide design and decision guidelines for sustainable cities," and thus has proposed the idea of infrastructure ecology to capture and analyze the intricacies of urban infrastructure systems (Xu et al. 2012). With this proposal, they have also offered a number of research questions fundamental to infrastructure ecology. These questions raise issues with how to translate ecology to infrastructure, the scale at which these analogies can be applied, the fundamental structure of urban systems, and new ways to organize infrastructure that can be tested and compared with one another (Xu et al. 2012). Furthermore, 12 major principles of infrastructure ecology have been proposed by Pandit et al (Pandit et al. 2015). These principles center around the integration of systems, synergizing between engineering and ecological systems, and considering socioeconomics and stakeholder preferences in all designs and decision. They provide guidance into how to think about infrastructure design and implementation. However, these principles have not been tested or incorporated beyond the ideation phase, and therefore their impact has yet to be seen.

There is a clear need to move towards more sustainable cities, and this starts by adequately understanding the resource usage and requirements of these areas. The "eco-city" model, as proposed by some, is focused on sustainable city development through transport, planning, and urban infrastructure but is more qualitative than quantitative (Anastasiadis and Metaxas 2013; Kenworthy 2006; Tsolakis and Anthopoulos 2015). Within the umbrella of the "eco-city," there are many nuanced sustainability ideas such as green urbanism (Anastasiadis and Metaxas 2013), green infrastructure (Ahern 2007; Tzoulas et al. 2007), and landscape ecology (Wu 2008). These concepts seek to understand the intersection of the ecological and socioeconomic components of cities, by incorporating the living environment into the built environment with a focus on ecosystem services provided by the living spaces within cities. These planning concepts are useful as a guide toward sustainability, but lack in quantitative measures to fully encapsulate sustainable development. However, other concepts have been developed to provide that quantitative need.

Two of these methods for cities are Material Flow Analysis (MFA) and Urban Metabolism (UM). At a basic level, both of these look at the flows of material and energy that enter and exit an entity, in this case cities. A MFA of the 25 highest population cities was able to determine water as a critical resource due to its need to be regionally available.

Additionally, atmospheric pathways played a large role in the transmission of carbon and nitrogen due to emissions of vehicles and industries. While small towns are limited by their local resources, these large cities are only limited by global resources, and that global maximum is yet to be fully understood. As that limit is approached "insight from the structure and function of wild ecosystems will be essential for insuring the stability and persistence of urban ecosystems" (Decker et al. 2000). Additional studies describe urban material and energy flows, with subsequent recommendations to increase recycling, decrease extraction of physical resources, and increase the efficient use of materials (Alfonso Piña and Pardo Martínez 2014; Huang and Hsu 2003). The main benefit of MFA is that it allows simplification of the complex flow of resources through urban areas and the coupling of these flow with the natural world through ecological services (e.g. water filtration) and resource extraction (Hodson et al. 2012). Urban metabolism takes this a step further by attempting to draw the parallel between cities and biological processes by quantifying "the technical and socioeconomic processes that occur in cities, resulting in growth, production of energy, and elimination of waste" (Kennedy et al. 2007). Studies of UM have been helpful in identifying the resources needed for a city to function (similar to nutrients of biological metabolism) (Kennedy, Pincetl, and Bunje 2011) as well as assessing how cities change over time in regards to their consumption and output (Sahely, Dudding, and Kennedy 2003).

While these are useful methods for quantifying the flows around systems, neither of these methods provides actual analysis as to how to improve these systems. Both are simply accounting methods that can highlight where resources are being used but do not provide consistent solutions to excessive resource use and waste generation. A review of over 100 UM studies showed there is a large variance in how these studies are done, and there is still room for improvement in this method, with one of the main challenges being "how to model the system's network" and realize "its effects on the environment" (Beloin-Saint-Pierre et al. 2015). Additionally, UM has been criticized for modeling a city a single organism, when in reality it functions much more like an ecosystem that consists of a network of organisms (Golubiewski 2012). Therefore, there is a need to improve both the modeling techniques of human-designed systems and the analysis that follows to provide the best understanding and suggestions for improvement. This dissertation proposes using natural ecosystems and the associated analysis for these systems.

2.3 Ecosystems and Food Webs

Ecosystem analysis stems from input-output analysis developed for use in economic analysis (Leontief 1936, 1951, 1966). This input-output analysis was first applied to ecosystems by Hannon to determine energy flows among the organisms in a system (Hannon 1973). All actors within the system are comprised of both an input and output environ (Patten 1978). This input environ comprises all flow that enters that actor while the output environ comprises all flow that exits that actor. Some of those inputs originate from other system compartments and some are from external to the system. Similarly, some of the outputs from a compartment may terminate as the input to another compartment or they may leave the system entirely. This complete collection of inputs and outputs around each compartment are linked together to create the entire system. For ecosystems, this is often represented as a directional graph (or digraph) to represent the structural connections as well as the amount of flow exchanged between compartments (Fath and Patten 1999b). This graph creates the Food Web of the ecosystem.

2.3.1 Ecological Network Analysis

Figure 2 shows two different graphical representations of an ecosystem. In each instance, the flows entering or leaving a compartment that are not connected to another compartment are external to the system. The top ecosystem shows dissipation of flow as the ground symbol, but does not include a storage term. The bottom ecosystem does not show this dissipation, but includes storage values within each actor. Visually, this allows one to understand the ecosystem structure at a high level. With networks of this size, it is easy to quickly identify cycles that are present and flow magnitudes that are greater than others. However, most ecosystems of are much greater size and complexity. As ecologists begin to create methods to understand ecosystems, a number of tools and metrics were developed that are now grouped under the umbrella term Ecological Network Analysis (ENA). ENA is a method developed by ecologists to understand and analyze ecosystems by measuring the flow of energy or materials between organisms to model and extract insights into the health, maturity, and overall function of these systems (Ulanowicz 2004). Using the flows between organisms, as shown in Figure 2, allows one to put quantitative measures to the cycling, structural information, and other key elements of these systems. ENA and many of the metrics used will be fully defined in the chapters that follow.

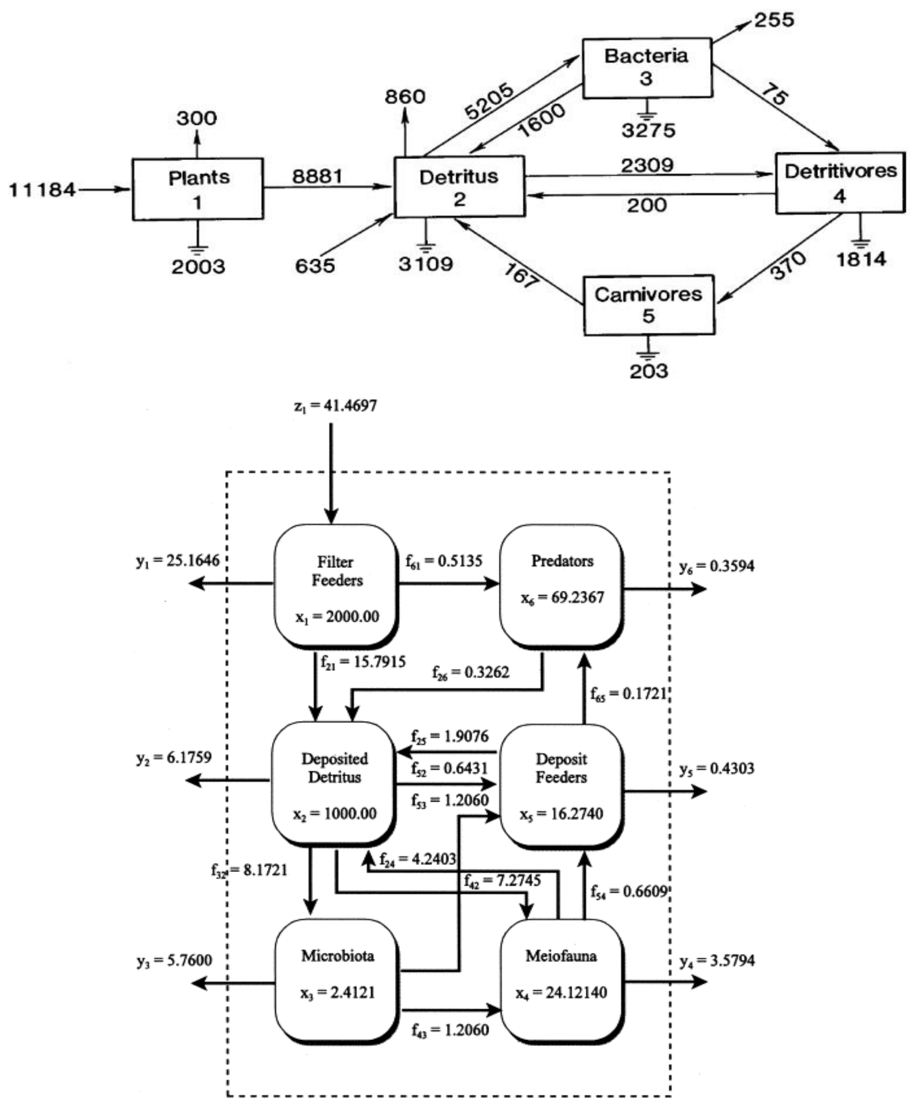


Figure 2 Network representations of two simple ecosystems. The top ecosystem shows ground symbols to represent dissipation in the actors (Ulanowicz 2004). The bottom ecosystem shows numbers within each actor representing a storage component (Fath and Patten 1999a).

2.3.2 *Ecological Network Analysis applied to human-designed systems*

In the previous decade, ENA has become increasingly popular for use in analysing human-designed systems. It has been used for water networks, energy networks, industrial systems, production and manufacturing networks, and emissions networks. This section provides a brief summary of many of these studies. Shown in Figure 3 is the network from one study that analyzed an urban water metabolic system (Zhang, Yang, and Fath 2010). Many of these studies look to characterize the metabolic structures of these systems, similar to that of an natural ecosystem (Briese et al. 2019; Liu et al. 2018; Lu et al. 2015; Meng et al. 2019; Tan et al. 2018; Yang et al. 2014; Yang and Chen 2016; Zhang et al. 2014; Zhang, Yang, Fath, et al. 2010; Zhang, Yang, and Fath 2010). The goal of this is to identify the hierarchy that exists within the systems similar to the different trophic levels in a natural system. Other studies use the ecological metrics that have been developed, and those are outlined in more depth below.

Through the study and analysis of 48 EIPs using ecological principles metrics, it has been shown that these systems do not perform as well as natural food webs. They lack both the complexity and functional roles of natural ecosystems (Layton et al. 2016b). Given this lack of complexity, Layton et al. attempted to combine EIPs together to increase the complexity of these systems to better mimic natural ecosystems. It was found that simply adding connections is not enough to improve the performance of the EIPs relative to the natural ecosystems, but instead, meaningful connections, such as the inclusion of detritus actors and decomposers (organisms that break down dead organic matter into usable material for plants), must be made to improve performance (Layton, Bras, and Weissburg 2017).

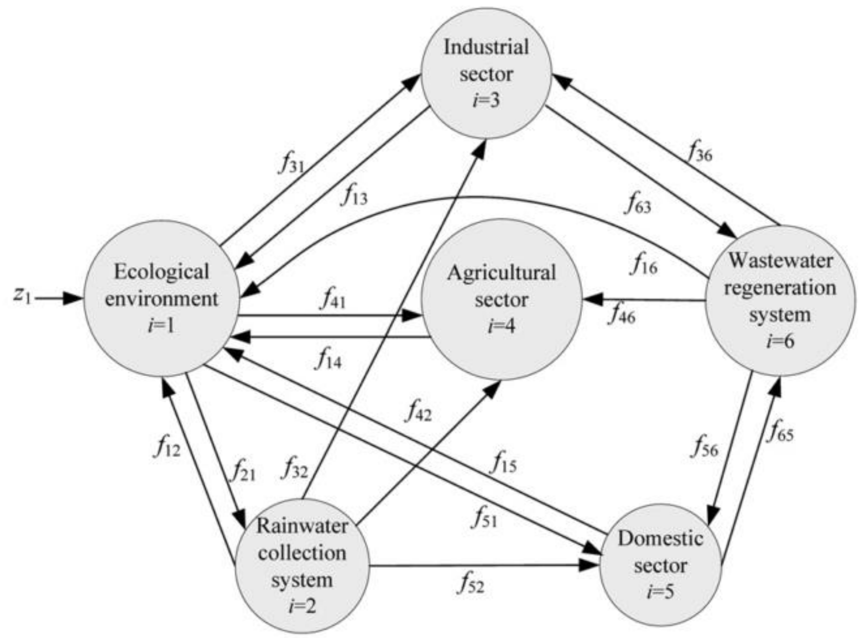


Figure 3 Ecological network model of urban water metabolic system (Zhang, Yang, and Fath 2010)

An analysis was conducted around a water network in The Nenjiang River Basin in China using ENA. This 10 network system included precipitation, river, groundwater, water allocation, evaporation, water treatment, agriculture, wetlands, domestic, and industry actors. This analysis used Robustness, Utility, and Control analysis within ENA. They showed how the Robustness changed over a 9 year window, generally showing an upward trend. Additionally, they analyzed different hypothetical scenarios related to changes in precipitation, water allocation, and supply and demand. It was found that “increasing farmland return water and restoring natural methods of wetlands water recharge will be crucial to maintaining the stability of the water system” (Meng et al. 2019).

Researches used ENA to analyze energy-water nexus networks of the Beijing-Tianjin-Hebei region of China. This study used a 42 sector network that were aggregated into 7 sectors that include agriculture, mining, manufacturing, electricity and gas supply, water supply, construction, and services and transport. It showed how each of these sectors contributed to the Finn Cycling Index within the water and energy networks of each area. Also, the Robustness of each of these networks is shown, showing all to be on the redundancy side of the curve (Wang and Chen 2016).

Kharrazi et al. used ENA to analyze a water network across multiple years in the Heihe River basin in China. This network comprised of 8 actors that included precipitation, groundwater, agriculture, landscape, industry, households, and two different sections of the river. They analyzed the changes in efficiency (Ascendancy) and redundancy (Overhead) as well as the total system throughput across these years the understand the changes that occurred in the system. It is shown that the efforts to increase efficiency have been successful although this has a negative effect on the redundancy (Kharrazi et al. 2016).

A 6 actor network of the Beijing economy was analyzed with ENA. This network included industry, agriculture, construction, transportation, post, and telecommunication, commercial and catering trade, and other services. This study analyzed this network across all years from 1985 to 2010. The researchers found that over this time span, the economic system grew exponentially but there was no trend in that development. Additionally, it is suggested to increase the Ascendency of this network if the goal is to match ecosystems as this economic network has a much lower Ascendency to Development Capacity ratio when compared to natural ecosystems. However, it is unclear whether economic systems should aim for the same optimal point that ecosystems inhabit (Huang and Ulanowicz 2014).

Researchers used ENA to analyze embodied carbon flows in socio-economic networks in different regions of China. They showed how Robustness could be used to help reach carbon reduction targets through the understanding of how carbon flows are concentrated along production pathways. Those regions with high Robustness have carbon flows that are very concentrated amongst a few pathways, while those with low Robustness have carbon flows that are more dispersed amongst the pathways. Thus, this can better inform the policy on how to decarbonize these regions by focusing either on a pathway specific or more unilateral approach that addresses all pathways (Fang and Chen 2019).

Lu et al. analyzed an EIP in Beijing with carbon flows using ENA. This system consisted of 6 actors which were energy providers, construction and infrastructure sector, residential housing sector, industry and business sector, waste management sector, and landscaping. The ENA was performed on this network as well as an additional network that included the external environment. The network including the external environment had greater ecological performance than the network that did not. ENA was also used to identify the major contributors of carbon emissions through both direct and indirect pathways and how these actors interacting with one another (Lu et al. 2015).

A study was conducted on water flow networks in the Yellow River Basin in Chin. This study examined 6 subsystems of the river basin across a 9 year window using a 13 node network including agriculture, industry, water purification, water distribution, and residential and commercial areas. The study compared these subsystems based on Ascendency and Redundancy, showing these systems tended to have a higher degree on organization and constraint when compared to natural ecosystems (Li, Chen, and Yang 2009).

Liu et al. conducted and ENA of greenhouse gas emissions metabolism systems in Saskatchewan, Canada. This study used a 13 sector network that included agriculture, mining, gas and oil extraction, coal production, power generation, construction, transportation, trade, and household consumption. They compared many different scenarios investigating different combinations of emissions and emission sources. All of the scenarios were found to have a high degree of redundancy with low efficiency meaning there were many alternative emission pathways (Liu et al. 2018).

2.3.3 Conclusions from previously analyzed systems

By analysing these studies, there are a few general observations that can be made. The first is about the networks themselves. The networks in the literature shown here typically have less actors than the ecological systems analyzed. Additionally, these actors are usually aggregated economic sectors like those shown in Figure 3, and include a lot of industry and manufacturing. This trend in the networks is likely due to data limitations as these large aggregations are often the only scale at which data sources are available. This analysis is limited by these smaller, aggregated models as they do not fully represent the real world interactions of these systems. They often ignore many of the vital connections that are present and should be analyzed in tandem with the systems. Mainly, they do not integrate the surrounding city infrastructure including the residential and commercial actors which would help to increase complexity.

The exact ENA metrics used are typically limited to a few specific types of analysis in each study. This analysis is often accompanied by other forms on analysis such as an Input-Output Analysis or embodied energy calculations. There is very little comparison of these systems to natural systems or even other human-designed systems. There is also no mention of using ENA as a design tool to improve the systems. These studies are fairly limited in scope, only highlighting a few of the ENA metrics, with a greater opportunity to expand the networks analyzed and the metrics that are used.

2.4 Summary of Literature Review

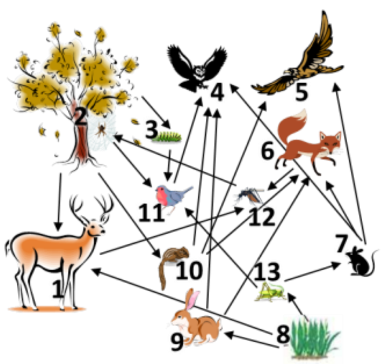
This chapter provides a brief introduction into sustainable design, bio-inspired design, and different techniques for analyzing systems. These different techniques have some shortcomings that ENA can address. ENA used for human-designed systems furthers the ideas of Industrial Ecology, Material Flow Analysis, and Urban Metabolism by providing a systems level, quantitative analysis. This analysis has been increasingly used to understand human-engineered systems, including many different types of networks and metrics. Given this diversity of use, there is an opportunity to synthesize the metrics, networks, and forms of analysis to create overall conclusions into how human-designed systems operate compared to natural systems and to one another. The next major step in this is to use this analysis to generate design principles that can be used across industrial and urban network design, which is a major goal of this dissertation.

CHAPTER 3. ECOLOGICAL NETWORK ANALYSIS

This chapter examines ENA and how ecosystem modeling relates to modeling of human-designed systems. It shows all of the definitions and formulas for the ENA metrics and what these mean from a natural and human-designed network perspective. This chapter also examines the analogy between ecological and human-designed systems. It is important to analyze the similarities and differences between these two kinds of systems to understand how ENA can be applied to both and the best ways to mimic ecosystem functionality.

3.1 Ecological Network Analysis

Ecological Network Analysis was developed to understand whole-ecosystem dynamics (Ulanowicz 2004). This analysis, based around graph, network, and information theory, models ecosystems as a series of nodes and edges. ENA aggregates organisms together into actors (species) that are defined by what they consume and what consumes them, such that each actor (species) is a node and the edges represent consumption. The resulting topology describes the “food web” that is the basis of ENA (Ulanowicz 2004). The edges and nodes can be represented as a square matrix with the edges given values to quantify amounts that flow from one node to the next. Figure 4 shows a graphical example of a Food Web and the corresponding structural matrix that represents it. This structural matrix (known as the adjacency matrix) is made of the predators and prey defined by numbers. In the matrix, a 1 represents an interaction between organisms where the column (predator) is consuming the row (prey), while a 0 represents no interaction. Modeling the ecosystem in this way, a number of metrics have been defined to determine the health, maturity, and overall function of the system. These metrics include both structural and flow based calculations that give different insight into the networks and have different data requirements.



$$
F = \begin{array}{c|c}
 & \text{predators} \\
 & \begin{array}{ccccccccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 \end{array} \\
\text{prey} \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \\ 10 \\ 11 \\ 12 \\ 13 \end{array} &
\left[\begin{array}{ccccccccccccc}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
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0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0
\end{array}\right]
\end{array}
$$

Figure 4 Network graph representation of ecological Food Web (Layton et al. 2017)

3.1.1 Structure Based Ecological Metrics

The ecological metrics based around structure are the easier ones to calculate. All that needs to be known for these is how the network is connected shown by the binary matrix in Figure 4.

Number of Species (N) is the total number of species or actors in a system. It can be represented by the number of rows or columns in the square adjacency matrix (Briand 1983). This has the same meaning for both ecosystems and human-designed systems.

Links (L) is the total number of direct links between actors in a system. This is shown by all of the non-zero terms in the adjacency matrix (Briand 1983). In ecosystems, a link occurs when one actor consumes another. In human-designed systems, a link can represent any exchange of resource and may not directly represent consumption.

$$L = \sum_{i=1}^{m}\sum_{j=1}^{n} f_{ij} \tag{1}$$

Prey (n_{prey}) are actors that are consumed by at least one other actor. This total number of prey is shown by the number of non-zero rows within an adjacency matrix (Schoener 1989). In human-designed systems, these actors provide a resource to another actor. This can be defined as producers or suppliers.

$$f_{row}(i) = \begin{cases} 1\ for\ \sum_{j=1}^{n} f_{ij} > 0 \\ 0\ for\ \sum_{j=1}^{n} f_{ij} = 0 \end{cases} \tag{2}$$

$$n_{prey} = \sum_{i=1}^{m} f_{row}(i) \tag{3}$$

Predator ($n_{predator}$) are actors that consume at least one other actor. This total number of prey is shown by the number of non-zero columns within an adjacency matrix (Schoener 1989). In human-designed systems, these actors take a resource from another actor. This can be defined as consumers.

$$f_{col}(j) = \begin{cases} 1 \; for \; \sum_{i=1}^{m} f_{ij} > 0 \\ 0 \; for \; \sum_{i=1}^{m} f_{ij} = 0 \end{cases} \tag{4}$$

$$n_{predator} = \sum_{j=1}^{n} f_{col}(j) \tag{5}$$

The *Prey to Predator Ratio* (P_R) is very simply the ratio of the number of actors that are consumed to the number of actors that consume. This speaks to the efficiency of energy use within a system, especially urban systems. Too many producers (or prey) will mean there is too many resources available that will not be fully consumed. Too many consumers (or predators) leads to a dependence on imports (Bodini and Bondavalli 2002). In both ecosystems and human-designed systems, this ratio should be balanced as to not put too much stress or reliance on a small subset of actors. One common example would be an energy network that is wholly dependent on a single power plant. In this case, the power plant is the sole prey, while all other actors depend entirely on that source.

$$P_R = {}^{n_{prey}}/{}_{n_{predator}} \tag{6}$$

Generalization (G): is the average number of prey consumed per predator in a system. This is calculated by dividing the total number of links in the system by the number of predators (Pimm 1982; Schoener 1989). This has the same definition for human-designed systems.

$$G = {}^{L}/{}_{n_{predator}} \tag{7}$$

Vulnerability (V) is the average number of predators per prey in a system. This is calculated by dividing the total number of links in the system by the number of prey (Pimm 1982; Schoener 1989). This has the same definition for human-designed systems.

$$V = {}^{L}/{}_{n_{prey}} \tag{8}$$

Linkage Density (L_D) is a measure of the level of structural connection within a network. It is simply the number of links divided by the total number of actors (Fath and Halnes 2007).

$$L_D = {}^{L}/_{N} \tag{9}$$

Connectance (C) is the number of actual direct interactions (L) in a FW divided by the total number of possible interactions (N^2). If one forbids cannibalism, then the number of possible interactions is diminished, resulting in the denominator becoming the fraction of non-zero off-diagonal elements in the FW (Briand 1983; Warren 1990; Yodzis 1980).

$$C = {}^{L}/_{N}\,2 \tag{10}$$

Specialized Predator Fraction (P_S) is the ration of specialized predators to the total number of predators. A specialized predator is an actor that only feeds on one other actor (Layton et al. 2017). This is important as it highlights a potential vulnerability within the system. If this is high, the system has a large reliance on single source interactions that if disrupted, could lead to issues within the system.

$$f_{s-col}(j) = \begin{cases} 1\ for\ \sum_{i=1}^{m} f_{ij} = 1 \\ 0\ for\ \sum_{i=1}^{m} f_{ij} \neq 1 \end{cases} \tag{11}$$

$$n_{S-predator} = \sum_{j=1}^{n} f_{s-col}(j) \tag{12}$$

$$P_S = {}^{n_{S-predator}}/_{n_{predator}} \tag{13}$$

Cyclicity is a structural measure of cycling. It is calculated by finding the maximum eigenvalue of the adjacency matrix **[A]**. The adjacency matrix, show in Figure 4, is the binary matrix representing the connections between all actors in a network. A Cyclicity value of 0 means there is no cycling present, a value of 1 means there is weak cycling with the presence of a single loop, and a value greater than 1 indicates stronger cycling with more loops leading to a higher value (Fath and Halnes 2007). Cycling is critical to the function of ecosystems as it allows for finite resources to be utilized multiple times over. This is also true of human-designed systems, although it is not as utilized. A higher number of loops means there is less dependency on outside resources, reducing the inputs to operate a system. Additionally, this may lead to a reduction of waste generated that is kept within the system as well as exported.

$$\det(\boldsymbol{A} - \lambda \boldsymbol{I}) = 0 \tag{14}$$

A *Strongly Connected Component* (SCC) is a subset of a system in which every node can be reached by every other node and the path will cycle back to the original node. If only one SCC exists in a system, all nodes are accessible by all other nodes (Allesina, Bodini, and Bondavalli 2005). These components are critical to understanding the cycling compartments of a system. Cyclicity is bounded by the number of nodes in the largest SCC.

Additionally, the largest eigenvalue amongst subcomponents will be the largest eigenvalue for the entire network (Fath and Halnes 2007). Networks can be split into multiple SCCs of different sizes representing small cyclic subsets of the larger network. A system with no cycles will exhibit no SCCs. There is not a direct calculation for this metric, but instead is calculated from algorithms. For this dissertation, the built in MATLAB function *graphconncomp* is used to calculate.

3.1.2 Flow Based Ecological Metrics

Flow based metrics provide a richer analysis of networks by quantifying connections. In ecological networks, the flow measured is either energy or mass that is transferred between organisms through consumption and decomposition (Ulanowicz 2004). However, the calculations are agnostic to what flow is being measured and therefore any unit of flow can be used for analysis with the caveat that it must be a consistent unit throughout the system. This is what is known as a common currency. This is a major difference between the structural and flow based analysis. In the structural analysis, all connections can be shown, regardless of what resources are being exchanged between actors. The same structural matrix could be separated into multiple flow matrices if there are multiple flows present. For example, a city network may have water, energy, and carbon flows present within the structural matrix. This could either be split into three separate flow matrices, or a common currency must be established to represent all flows. This currency could be some equivalent currency such as carbon or coal. Using a common currency presents a few issues that are discussed more in detail later. Including the flow information as increases the amount of information needed substantially.

To incorporate more information into the flow based analysis, this uses a larger matrix than the structural one. This matrix includes three additional sets of information that represent the imports, exports, and dissipation of resources outside the system. These are added to the internal transfers characterized in the adjacency matrix to create an $N+3$ x $N+3$ flow matrix **[T]** shown in Figure 5 with N being the number of actors in the system. The first row in this matrix (row zero) represents the imports of resources to the system into the different actor compartments of the systems. The second to last column (N+1) represents exports from the actors in the system to external sources. Finally, the last column (N+2) represents the dissipation or respiration losses from actors in the system. The additional rows and columns that are added as a result to keep a square matrix are filled in with zeros and do not represent anything. The difference between exports and dissipation is subtle but important. Exports are useful resources that leave the system that could be recoverable and are used by an actor outside of the system. An example of this would be sheets of metal that are sold to an actor outside of the system. Another example would be water lost due to a leaky pipe. Dissipation are any flows that are not recoverable that are a result of processes within the system. An example of this would heat lost through the generation of electricity or water that evaporates in a reservoir. A flow from one actor to another is shown by a value populated in the corresponding row and column (*i* and *j*) which is represented by t_{ij}. If there is no value for t_{ij} this means there is no connection present.

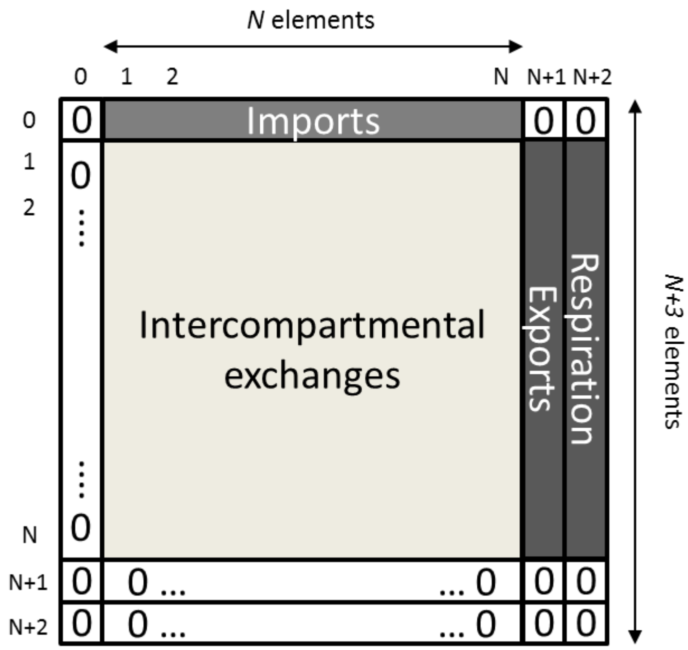


Figure 5 Squared (N+3) x (N+3) flow matrix [T]

Total System Throughput (TST_P) is the sum of all flows into, within, and out of a system. It is a measure of the total amount of medium that is processed in some way. It represents the total activity, and can be used to compare system sizes (Ulanowicz 1986).

$$TSTp = \sum_{i=0}^{N+2} \sum_{j=0}^{N+2} t_{ij} \tag{15}$$

Finn Cycling Index (FCI) is a measure of the amount of flow that is present within the cycling loops of a system. It is calculated by looking at the flow being cycled in the system and normalizing it with the total flow of the system (Finn 1980). As previously established with Cyclicity, the cycling of the network is important to quantify. To maximize this would be to maximize the amount of flow that stays within the system bounds and decrease the amount that is imported or exported. Thus, this could lead to a reduction on reliance on imported resources and an increase in utilization of resources already present within the system. From an urban and industrial perspective, this could be seen as recycling rate.

$$TST_C = \sum_{j=1}^{n} \left(\frac{t_{jj} - 1}{t_{jj}} \right) T_j \tag{16}$$

$$FCI = \frac{TST_C}{TST_f} \tag{17}$$

Mean Path Length (MPL) is calculated by dividing the total system through flow by the inflow into the system (Finn 1976). It measures the number of compartments visited by a flow before exiting the system, but also measures the system activity caused by the input to the system (Fath et al. 2019). From a human designed perspective, this could be described as resource utilization. The more compartments a flow visits, the more utilized that flow becomes because multiple actors are able to see benefit from it. However, this is influenced by network size as large networks will have a higher potential number of actors that can use the same resource. More actors visited could also translate to a less efficient system as there are more steps between the initial input and the final consumption. It is therefore critical to understand why a resource would visit multiple compartments to understand the importance of MPL.

$$MPL = \frac{TSTf}{\sum x_i} \tag{18}$$

Shannon's Index (H) is a measure of the diversity of flows within a network (Shannon 1948). This was first applied to ecosystems by MacArthur who sought to quantify flow diversity in natural systems (MacArthur 1955). This measure is the foundation of the information based metrics that are shown following.

$$H = -k \sum_{i=0}^{N+2} \sum_{j=0}^{N+2} \frac{t_{ij}}{TSTp} \cdot log_2 \left[\frac{t_{ij}}{TSTp}\right] \tag{19}$$

Average Mutual Information (AMI) is a measure of the constraint and organization in the system. Based on information theory, AMI quantifies the amount of flow that is structurally constrained, defined as the number of existing flow paths. A network where there are limited pathways through which a quanta of substance can move is more constrained. This has been seen as a measure of ecosystem development because a more constrained network will be less redundant and more efficient (Bodini, Bondavalli, and Allesina 2012; Odum 1969). In the formula below, k is a scalar value that is usually set to one to calculate this metric (Ulanowicz 2004). Higher values for AMI mean more constraint in the system, such that the medium is being processed more efficiently. Constraint in this context is defined by the number of paths a flow can take leaving an actor. Flows that have more potential pathways are less constrained, while those with fewer potential pathways are more constrained. A highly constrained system (high Ascendency) is seen as having high efficiency as well due to the predictable nature of where flows will go through the system.

$$AMI = -k \sum_{i=0}^{N+2} \sum_{j=0}^{N+2} \frac{t_{ij}}{TSTp} \cdot log_2 \left[\frac{t_{ij} \cdot TSTp}{\left(\sum_{j=0}^{N+2} t_{ij}\right)\left(\sum_{i=0}^{N+2} t_{ij}\right)} \right] \tag{20}$$

Ascendency (ASC) is directly related to the AMI, and is calculated by setting the scalar value k in the calculation for AMI to the value of the total system throughput, thus providing physical units to the system activity. This measures how well a system is "performing at processing the given medium" (Ulanowicz 2004). It was initially believed that this value would always increase as ecosystems developed, but it has since been said that there is simply a propensity for these systems to have higher ascendency (Ulanowicz 1997). In essence, this is a non-normalized version of AMI, meaning this does not provide much insight when comparing between networks.

$$ASC = AMI \cdot TSTp \tag{21}$$

Development Capacity (DC) is the maximum value for ASC and it is a measure of the flow diversity normalized by the total system flow. It measures the maximum potential for improvement of a system in terms of constraint and efficiency (Bodini et al. 2012; Ulanowlcz and Norden 1990). Thus, the ratio of ASC to DC (ASC/DC) can be seen as a measure of system efficiency compared with the maximum efficiency that could be achieved. This is not efficiency in a traditional engineering definition, but rather one that is based on flow constraint.

$$DC = -1 \cdot \sum_{i=0}^{N+2} \left[\left(\sum_{j=0}^{N+2} t_{ij} \right) \cdot log_2 \left(\sum_{j=0}^{N+2} t_{ij} \right) \right] \tag{22}$$

$$DC \geq ASC \geq 0 \tag{23}$$

Overhead (Φ) is very closely related to ASC and DC. This is also known as reserve and is a measure of the amount of reserve of flexible actions the system has access to in order to respond to change. The total capacity for self organization of the system (DC) is the sum of the constrained flow (ASC) and the additional unordered flow (Φ). Overhead can therefore be calculated by subtracting ASC from DC (Ulanowicz et al. 2009).

$$DC = ASC + \Phi \tag{24}$$

Robustness (R) is a metric related to the efficiency and redundancy of a system. In all networks, there is a tradeoff between these two characteristics, and Robustness measures that tradeoff, also known as the tradeoff between effective performance and reserve capacity. Robustness is often plotted alongside the ratio of ASC to DC to visualize this tradeoff. Previously analyzed natural ecosystems fall within a range of values for Robustness known as the "window of vitality" showing there is an ideal tradeoff between efficiency and redundancy in the ecological world (Ulanowicz et al. 2009). This metric takes into account many of the nuances of network dynamics and is related to the overall system resilience. Systems that exhibit a high degree of ASC relative to the maximum are considered to be brittle and vulnerable to failing. Meanwhile, systems that exhibit too little ASC may be overly redundant and not able to effectively move resources (Ulanowicz 2000). In this way, different systems may be designed to value either efficiency or redundancy, and therefore it is hard to assign an ideal value for Robustness. Regardless, this metrics speaks to those tradeoffs mentioned and can effectively be used to describe the priorities of a particular human-designed network.

$$R = -k\left(\frac{ASC}{DC}\right)\log_2\left(\frac{ASC}{DC}\right) \tag{25}$$

3.2 Analogy of ecological and human-designed systems

Very simply stated, ENA can analyze any system modeled as shown. However, it is important to understand how closely that system operates compared with an ecological one due to the analysis being based around ecosystems. In this dissertation, there is an analogy made between natural and human-designed systems. At a high level, these systems contain actors that share resources through production and consumption. There are inputs, outputs, and dissipation in both. This section goes deeper into that analogy to understand the fundamental similarities and differences between these two system types and how those can potentially impact the final results.

3.2.1 Compensatory Flows

To start, it is important to understand why interactions occur within these two types of systems and what could be considered the main driving factor. Within human-designed systems (especially economic systems), there is a compensatory flow associated with any exchange of resource or service. This compensatory flow is often some sort of monetary or other useful counterflow to "pay" for the resource or service. These types of flows do not exist in the same way in ecological systems. Mostly what exists are uncompensated predator-prey relationships where the exchange is purely one way with one actor benefitting and the other actor is negatively impacted (Ulanowicz and Puccia 1990). This difference in compensation fundamentally changes the reason for exchanges to occur. In ecosystems, organisms make decisions based on their own survival, regardless of the negative effects it may have on other organisms. In human-design systems, exchanges must be agreed upon by both parties. Interactions are actively sought out that will reduce the amount of resources an actor has, so that it can gain another resource, usually in the form of currency. This means for every human system that is modeled, there is an equal and opposite system that could be modeled using that counterflow. Exchanges can occur that may not seem advantageous from an ecological perspective and would never occur in a natural system. This provides a driving factor within the human-designed systems that is not present within natural ecosystems.

3.2.2 Scale

The scale of these two types of systems are dramatically different. Ecosystems likely have billions of organisms if every individual microorganism is included. While there is an uncountable number of actors, the average size of each is relatively small. Conversely, human-designed systems consist of much fewer but much larger actors. A population center may span 10 miles but still be considered a single actor. With these larger actors, the exchanges between them are much larger as well. The energy needed to power a city dwarfs the energy exchange between two organisms, regardless of their size. This larger scale means that smaller interactions become negligible in the human-designed systems. This also means there are different levels of aggregation.

3.2.3 Resources

Natural ecosystems are limited by the natural resources available to organisms. These resources mainly involve the nutrients such as nitrogen and carbon that are present within the biotic and abiotic parts of the systems. The availability of those nutrients is affected by many factors including location, climate, and human influence. While outside resources can cross the system boundaries, most of these resources are contained within the ecosystem area. Human-designed systems are also limited by natural resources, but they have a much greater capacity for importing external resources. This means water or food can exist in desert regions where they would not naturally occur. As mentioned previously, a resource that exists in human-designed systems but not in ecological ones is monetary currency. There are also nonphysical resources such as information, digital infrastructure, and human capital. This makes for a much more complicated system of systems.

3.2.4 Trophic levels and functional roles

Trophic levels are an important aspect of ecosystems, organizing organisms into a hierarchy based on their primary function roles (producer, consumer, or decomposer) (Lindeman 1942). This is not a perfect representation of the system as organisms can feed at multiple levels, but there are techniques to place organisms within these levels and it can nevertheless be useful to organize in this way (Ulanowicz 2004). There have been efforts to organize human systems in this same way (Briese et al. 2019; Zhang, Yang, Fath, et al. 2010; Zhang, Yang, and Fath 2010), but these trophic levels are assigned analytically, and it can be argued that these actors are not actually mimicking the roles they are assigned. Many of the actors both produce from raw materials and consume products from other actors. Additionally, there is not a clear decomposer role within the human systems, but this will be discussed in more detail later. There are not clearly defined predators and prey in these systems compared to the ecological ones. Two actors can exchange resources so that both consume and are consumed by each other. These types of interactions seldom occur in natural systems. This directly effects some of the metrics defined here, but also qualitatively highlights a difference in system functionality. In ecosystems, organisms want to only be predators and never prey. The opposite is true in human-designed systems. The actors in these systems grow and produce, with the explicit purpose of being consumed. That consumption is what leads to survival. The terminology is not one to one because there is a much different context.

3.2.5 Planned vs naturally occurring

Ecosystems are naturally occurring. They have developed over the entirety of Earth's history. While these systems are influenced by and must adapt to changes in the environment (such as new human development), they are wholly independent from any sort of design. As a result, the interactions that are created between organisms are not artificially enhanced in any way. What develops as a result is purely dependent on what will be most beneficial. In human-engineered systems, everything is designed and planned. These systems (especially urban and industrial systems) create a built environment in the natural one. As a result, connections can exist that would not be supported naturally. When analyzing these systems, it is important to realize that all interactions are artificial because they would not happen if not for human influence. This means designers and planners are responsible for the system dynamics. This presents a great opportunity to improve these systems based on analysis.

3.2.6 Governing principles and limitations

Natural ecosystems are primarily governed and hindered by the laws of thermodynamics. Energy cannot be created, nor destroyed, and the same goes for matter. This drives all interactions and limits the growth to a certain level. Human-designed systems are also limited by these laws, but are also governed in many more ways. There are political laws that prevent certain actions from being taken. Additionally, there are economics at play that may not outright prevent an action, but will strongly influence which actions occur. Actors in both are attempting to "survive," but survival of an industry looks very different than the survival of an organism. One needs to provide value and accumulate currency to survive while the other needs the basic resources of life.

3.2.7 Competition

Competition in the natural world relates to the consumption of resources. Many organisms may consume the same prey, thus leading to competition between them. When one organism succeeds, others are negatively impacted as they must now work harder to find food. In human-designed systems, competition is similar, but there is more potential for mutual success. When resources are exchanged between actors, both benefit in some way because of the compensatory flows mentioned previously. There are more opportunities for mutualistic relationships to exist because no actor would willingly make an exchange if it would not be to their benefit.

3.3 Scope and Limitations

With the main method for analysis established, it is important to understand the limitations that surround both that analysis and the systems to be analyzed in this dissertation. ENA is not an exhaustive tool that can examine and put quantification to every aspect of a system. It is limited to the data that it is given and also by what it was designed to do. Similarly, there are limitations to the system models themselves and many of these limitations are the same. As with all attempts to model systems, there are assumptions that must be made because every facet cannot be fully accounted for. This section mentions the major limitations and assumptions that are present throughout this dissertation.

3.3.1 System Boundaries and External Actors

As mentioned, when ecosystems are analyzed with ENA, they are limited to a specific geographic area. This same limitation is applied to the human-designed systems. In reality, supply chains and resources can extend around the globe, but this analysis is designed around local networks. As with all systems, where the boundaries are drawn can significantly change how the system is analyzed. Given this, the human-designed systems are limited to a specific region as much as possible. However, that region can vary widely between systems. It is impossible to create rules to fully encompass all of these systems so no definite rules are created here. Rather, networks are analyzed on a case by case basis to determine the local network. With these system boundaries drawn, there are certain actors that become external to the system. In ecological networks, the biggest outside influence is the sun which provides the basis of energy for all food webs. In human-designed systems, these outside actors are treated in much the same way as the sun. They provide what is needed to the network, but they cannot be changed. This is true of both the imported and exported resources and energy. In reality, these actors are not infinite sources and sinks that do not affect the network. This limits the analysis to what is specifically within the system boundary. This limitation ignores some of the critical connections that are crucial to system operation (such as the initial import of water into a city). However, some of these external actors cannot be changed (including the amount of precipitation). The focus on ENA are actors specifically within the system, so while this is acknowledged, the analysis is not suited to take into account external actors and is therefore not of big concern.

3.3.2 Data Availability

With all modeling efforts, there are limitations due to the data that is available. This dissertation does not analyze the data collected about ecosystems, as that is outside of the scope. It is assumed these networks have been correctly constructed. However, the issue of data availability is also present within ecosystems. Therefore, these flows are often estimated based on other information available such as density and feeding rate (Ulanowicz 2004). In reality, there will always be some error associated with these networks, but these networks are used to understand general trends which should remain consistent regardless of those small errors. The main focus of this limitation are the human-designed systems. At larger scales, there is a greater availability of data due to large aggregations, but at the city or industry level the amount of uncertainty increases dramatically due to a lack of data (Patrício et al. 2015). Often the city data is estimated from larger regional or country data, which does not provide a clear picture of the specific city of interest (Shahrokni, Lazarevic, and Brandt 2015). This lack of data limits the insight of this type of analysis due to the complexity of urban and industrial systems.

3.3.3 Simplified Models

Given the limited data and system boundaries, this leads to the creation of drastically simplified models of these systems. A model that is too simplified will not truly represent the system and may lead to incorrect interpretation of results or policy implications. As shown, these models are limited to two dimensional square matrices. They show a simplified version of the interactions between actors. These matrices ignore a lot of the complexity and system dynamics present within these networks. The models are static snapshots that aggregate dynamic systems across a given time range, usually a year. Because of this, some of the connections shown may not exist at all times within that range. This means the ENA metric results shown are constantly changing, but they are shown as static values in this analysis (Fath and Patten 1999b). There is also a question of scale and aggregation in these models. These systems lump compartments together for the sake of analysis, but the degree to which they are lumped can affect the results. This aggregation should be consistent within the model, but it may differ between models (Fath and Patten 1999b). While these simplified models inhibit the precision of the analysis, the results can still be useful as it is meant to understand systems at a high level.

3.3.4 Designing from Analysis Tool

ENA was designed around the analysis of ecosystems. As mentioned, ecosystems and the food webs within them are naturally occurring. There was no original design for where organisms would be placed and what would consume what. The goal is to use the results from the analysis to help design better human engineered systems. By taking an analysis tool and using it design, it is being used beyond its original intent. While it has been shown that there is some correlation between the ecological metrics and traditional sustainability metrics (Layton et al. 2016a), it needs to be further proven that ecological metrics are useful in the design process. This is one goal of this dissertation, but it is important to acknowledge this at the outset.

3.4 Conclusions and Summary

Ecological Network Analysis is a wide-ranging umbrella term for many different network analysis metrics. The metrics shown here represent a subset of those metrics that have been effectively used to analyze networks of all types, not just ecological ones. The definitions of these metrics differ when translated to human-designed networks, but can easily be applied to almost any system. Beyond the metrics themselves, there are some clear differences between natural and human-designed systems. These differences include the goals of the actors, how exchanges occur, and governing principles. Even with these differences, using ENA can still be beneficial to understand how the human-designed networks operate and compare with one another. In the following chapters, this analysis will be used with various systems, both ecological and human-engineered. It will be used to show trends among the systems, as well as quantitively measure some of the qualitative differences mentioned here between natural and human-engineered systems.

CHAPTER 4. ECOLOGICAL ANALYSIS OF URBAN-INDUSTRIAL ECOSYSTEMS

This chapter applies the ENA metrics to a set of Urban-Industrial Ecosystems (UIEs). These results are compared against previously analyzed Eco-Industrial Parks (EIPs) as well as previously analyzed Food Webs. Through this comparison, it is shown how the human-designed systems consistently perform worse based off these ecological metrics when compared with the Food Webs. Additionally, the UIEs are analyzed based on network type and actor type inclusion. This highlights the role certain actors play in processing material or energy in these systems.

4.1 Data

Data on coupled urban and industrial networks (Urban-Industrial Ecosystems; UIEs) were gathered by searching academic literature for urban metabolism and urban flow networks. Many of the networks came come a review of these studies (Beloin-Saint-Pierre et al. 2015), and the others came from references within these studies. Only networks with flow information were considered so that the full suite of Ecological Network Analysis (ENA) metrics could be used. In total, 13 different publications were used to generate 29 separate networks. Some data sources included multiple networks based on data from different years, locations, or the type of flow. The 29 networks varied in size from 3 to 16 actors. All networks were analyzed on a yearlong time scale and were bounded geographically at the city or regional level. These networks come from these references (Baker et al. 2001; Burström et al. 1997; Chen and Chen 2012; Forkes 2007; Hendriks et al. 2000; Lauver and Baker 2000; Liang and Zhang 2011; Nilsson 1995; Singh et al. 2001; Zhang, Yang, and Yu 2009; Zhang, Zhang, and Yang 2011; Zhang et al. 2016; Zhao 2012), and the flow matrix for each can be found in the Appendix in Figures 19-47.

Table 1 describes how key attributes, such location, flow measured, and specific actor type vary across the 29 networks. An agriculture actor is defined as any crop, meat, or dairy producer. This does not include actors that produce a relatively small amount of edible product such as backyard composting. An industry actor is defined as any actor that produces non-agricultural goods, such as lumber or steel. Specifically, these actors convert raw material into something useful for the system. These are different than commercial actors, such a retail store, because they transform material. A natural environment actor is defined as any natural area such as a river, the atmosphere, or a forest. Obviously, every network occupies a physical space, so this actor is always present, but this is only specifically called out when it interacts with the other actors in a meaningful way. Specifically within the nutrient networks, the natural environment plays a large role due to the organisms within the natural environment processing those nutrients. Finally, a utility actor is defined as any actor producing or distributing water, electricity, wastewater, natural gas, or any other critical resource (other than food).

These actors define important functional types participating in resource exchanges in human systems. Industry is a primary consumer of raw material in human-designed systems. Agricultural actors are one of the few actors that include living organisms and have a large potential to recycle nutrients that would otherwise be exported from the system. The natural environment is often excluded when analyzing urban and industrial networks, but it plays an important role in receiving most of the waste and dissipated resources from UIEs. Finally, utilities are an interesting actor to observe because they do not have a parallel in natural ecosystems, but they are essential in keeping other actors operational. There is no centralized system in place to provide energy and water. Therefore, this is one of the biggest differences between natural ecosystems and human designed systems and could show an area with the largest departure from natural systems.

Table 1 Number of Urban-Industrial Ecosystem networks with specific attributes

Attribute	**Number of Networks**
Location	
Asia	16
Europe	7
North America	6
Type of Flow	
Nitrogen	12
Energy	6
Emergy	4
Material	4
Phosphorus	2
Carbon	1
Includes Actor Type	
Industry	22 (76%)
Agriculture	16 (55%)
Natural Environment	15 (52%)
Utility	12 (41%)

As shown, the majority of these networks are located in Asia, with all but one of those being in China. Additionally, there are more nitrogen networks than any other network and about two-thirds of the networks include an industrial actor.

The type of flow is the final network characteristic and can be either a material substance or energy. The type of flow provides important potential insights since flow substance influences recyclability, amount of dissipation, which actors are capable of using which flows, and how these flows interact with the natural environment. The energy networks are broken into two categories of energy and emergy. The material networks are broken into nutrients (including 3 individual nutrient flows) and general material. The general material networks are those that measure a physical flow of material, such as wood or metal. Each of these networks come from academic literature and were created using information supplied by the original authors (e.g. flow magnitude, connectivity etc.). These networks were not independently verified, and therefore are assumed to be correct based on the assumptions and data from the original authors and references. While this provides a potential source for error in the final results, this study looks to identify overall trends in these systems as opposed to extremely precise numbers. Therefore, this is not of great concern.

UIE network properties were benchmarked against two other previously analyzed network types, EIPs and natural food webs (Layton et al. 2016b). The first dataset consists of 48 EIPs gathered from the literature. The second is a dataset of 31 published ENA studies of natural food webs. These Food Webs come from a package developed by Borrett for ENA (Borrett and Lau 2014). The Food Webs were extracted from the provided R code. Only 31 of the available Food Webs are used as these were all collected after 1993. As Layton shows, there was a change in the way this data was collected after 1993 and a large shift in the data, showing these systems to be much more accurate representations of the actual ecosystems (Layton et al. 2016b). These data provide a good baseline for how other human designed systems perform, as well as a comparison to natural systems.

4.2 Additional Metrics

In addition to the traditional ENA metrics defined in Chapter 3, a few additional, newly created metrics are defined here to be used in this analysis. These three metrics are modifications of other established metrics defined in Chapter 3. These modifications are meant to give further understanding that was not originally captured in the metrics they are based upon. It should be noted that these are not meant to supplement this analysis, but rather compliment it. These were developed with the human-designed systems in mind, and therefore may not be useful for ecologists in analyzing natural ecosystems. However, all metrics will be applied to both the human and natural systems. The hypothesis is that these metrics will help explain what makes a highly preforming system operate in the way that it does.

4.2.1 Percentage of Connecting Actors

As mentioned with Mean Path Length, the number of actors visited by a flow before leaving the system is of interest to ENA. The more actors visited, the greater potential for that flow to be fully utilized before expulsion. Also as mentioned, human-designed systems tend to be very linear in nature with many flows exiting the system after only visiting a single actor. The Percentage of Connecting Actors looks at the number of actors that lie on the shortest path between two other actors and compares this against the total number of actors in the system. The higher this percentage, the greater number of actors that play a part in resource transformation within the network. It is expected that this will be higher for the natural systems compared to the human-designed systems. This is a structural metric so only the adjacency matrix is needed to calculate it.

4.2.2 Single Source Percentage

This metric is a direct modification of the Specialized Predator Fraction. It takes all of the specialized predators and adds in the predators that are solely reliant on imports. The Single Source Percentage takes the total number of actors that rely either on a single prey or fully on imports and divides it by the total number of actors. This modification takes this beyond a structural metric to a flow based metric as the import row of the flow matrix is needed to calculate it. This was created because it is important to understand potential vulnerabilities in a system, and any actor that relies on a single source for resources will be vulnerable.

4.2.3 Normalized Standard Deviation of AMI

AMI measures constraint of the system and is one indicator of ecosystem development. Networks with high AMI are systems that have a large number of well connected-nodes with comparable size (Baird, McGlade, and Ulanowicz 1991). Each compartment has a contribution to the overall AMI. Therefore, systems with high AMI should have an equitable contribution of AMI from all of the actors. This can be tested by looking at the Normalized Standard Deviation of AMI. The standard deviation allows one to understand the spread of the AMI contributions across the actors. This must be normalized by the AMI to account for the difference in overall AMI between networks. As AMI is a flow based metric, this is also a flow based metric.

4.3 Results

The results shown here give a general idea of how the UIEs preform based upon ENA. All of the metrics are not shown in depth, but these values can be found in the Appendix in Tables 44-50. Rather, this chapter highlights some of the more interesting and meaningful results.

4.3.1 Comparison of Structural Ecological Metrics with Urban-Industrial Ecosystems with Eco-Industrial Parks and Food Webs

Structural properties of networks vary between human and natural systems, with the food webs showing greater connectivity and cyclic pathways (Figure 6). The average cyclicity is 1.75, 1.59, and 7.44 for the UIEs, EIPs, and Food Webs, respectively. The average linkage density is 2.07, 1.64, and 8.52 for the UIEs, EIPs, and Food Webs, respectively. As seen in Figure 6, the median and range of values for cyclicity are similar for the UIEs and EIPs, and much greater for the Food Webs. This is similar to the linkage density boxplot also shown in Figure 6 with the Food Web values far exceeding the values for the UIEs and EIPs. UIEs show substantial variation in structure and cycling potential; 6 had a cyclicity of zero (no cycles present) systems, 7 had a cyclicity of one (a single cycle present), and 16 had cyclicity values greater than one (multiple cycles present), with the highest cyclicity value equal to 8.77. This is higher than the average food web but still smaller than the highest natural system (a mangrove ecosystem in South Florida) cyclicity of 14.17. This same UIE showed the highest linkage density of 8.73, which was also higher than the average Food Web value, but smaller than the maximum value of 16.91. This highly linked and cyclic network is a material flow network around the city of Suzhou in China (Liang and Zhang 2011).

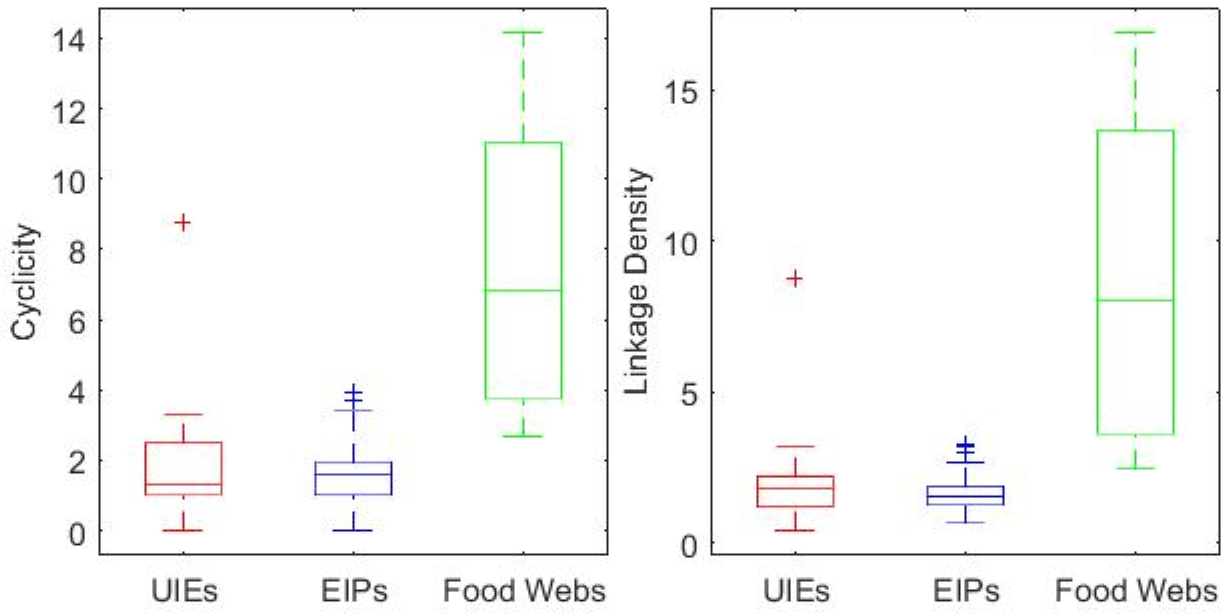


Figure 6 Comparison of Cyclicity (left) and Linkage Density (right) between Urban-Industrial Ecosystems, Eco-Industrial Parks, and Food Webs

Table 2 shows the average values for the other ENA structure metrics. As shown, there is a large disparity in the size of these systems based upon the number of actors and links. The Food Webs have an average of 55 actors while the UIEs have an average size of 8 actors and the EIPs have an average size of 12 actors. Additionally, the EIPs and UIEs average around 7 to 9 links while the Food Webs average close to 600. These size discrepancies are also shown in the Generalization, Vulnerability, and the numbers of predators and prey. The Prey Predator Ratio for all of the systems averages close to 1, with the Food Webs having a slightly higher value for this compared to the human-designed systems. Specifically, the EIPs have a value of 0.94. A value lower than 1 indicates a potential vulnerability in these systems as they have more consumers than producers. The

Specialized Predator Fraction shows a large difference between the natural and human-designed systems. The Food Webs have an average of 8.35% of predators that rely on a single prey, while the UIEs and EIPs have around 50% of specialized predators. The Percentage of Connecting Actors also has a large disparity between the Food Webs and other systems. The UIEs have the lowest value for this at 33.2% while the Food Webs have the highest at over 75%. Connectance is the only value where the human-designed systems out preform the ecological ones. This is to be expected given the size of the systems looking at the calculation of connectance. It is inversely proportional to the square of the number of actors and given the much larger size of the natural systems, this explains why this value would be lower for those. As shown, there are no other outliers in the UIE dataset of Figure 6. Excluding this one point, the UIEs have a Cyclicity that ranges from 0 to 3.28 and a Linkage Density that ranges from 0.58 to 3.19. This very closely mimics the ranges for the EIPs that have a Cyclicity range of 0 to 3.92 and Linkage Density range of 0.71 to 3.25. The similarity in ranges is seen across all of the structural metrics as shown in the Appendix in Table 46 and

Table 47.

Table 2 Average structure based ecological metrics for Food Webs, UIEs, and EIPs

	Food Webs	**UIEs**	**EIPs**
Actors	54.90	8.21	11.79
Links	573.35	20.72	19.31
Prey	51.74	7.10	8.77
Predators	47.35	6.93	9.77
Prey Predator Ratio	1.09	1.04	0.94
Generalization	9.64	2.44	1.94
Vulnerability	8.83	2.45	2.15
Connectance	0.17	0.30	0.17
Specialized Predator Fraction	8.35%	42.48%	52.73%
Percentage of Connecting Actors	76.81%	33.20%	51.28%

The results for the Strongly Connected Component analysis is shown in Table 3. This is a summary table of the information with the full data of all the networks shown in the Appendix in Tables 48, 49, and 50. The percentage of actors involved in cycling is around 50% for the human-designed systems and 77.53% for the ecological systems. All of the Food Web systems have at least one single SCC, 23 of the 29 UIEs have at least one SCC, and 42 of the 48 EIPs have at least one SCC. The average number of actors involved in an SCC is around 5 for the UIEs and EIPs and much greater at 43 for the Food Webs. This is only for networks that include a SCC meaning this is averaged by the 23 UIEs and 42 EIPs that include cycling. Due to the fact that the Food Webs are much larger, each system is normalized by the size of that system to compare among the datasets. The EIPs have the lowest normalized value, the UIEs are in the middle, and the Food Webs have the largest value. Finally, the average number of actors per SCC is shown. As seen in the Appendix in Tables 48, 49, and 50, 2 of the 31 Food Webs with a SCC have multiple with the rest only having a single. Similarly, 2 of the 23 UIEs have multiple SCCs. For the EIPs, 11 of the 42 have multiple SCCs. Therefore, the average number of actors per SCC is very similar for the Food Webs and UIEs, with a greater change for the EIPs.

Table 3 Average values for Food Webs, UIEs, and EIPs for Strongly Connected Component Analysis

	Networks with SCC	Average Number of Actors in SCCs	Percentage of Actors Involved in Cycling	Normalized Number of Actors in SCCs	Number of Actors per SCC
Food Webs	31	43	77.53%	0.748	42.68
UIEs	23	5.35	52.45%	0.628	5.13
EIPs	42	5.93	50.23%	0.505	4.85

4.3.2 Comparison of Flow Based Ecological Metrics of Urban-Industrial Ecosystems with Food Webs

Similar to the structural analysis, the human-designed systems perform worse than the natural systems for the flow based metrics, although the gap is not as dramatic. As shown in Figure 7, the median values for all of the flow metrics are consistently lower for the UIEs than the Food Webs. Additionally, the values calculated for UIEs have a greater range than those for the food webs. Thus, although the median values for UIEs are smaller compared to food webs, the maximum values are greater for both Average Mutual Information and Finn Cycling Index. This trend of a larger spread of the UIEs is also present in Robustness, shown in Figure 8. As mentioned, the “window of vitality” is where the green crosses occupy this curve. Many of the UIEs fall within the “window of vitality” (the peak of the robustness curve), although a considerable number of systems show either more constraints or more redundancy than is thought to be optimal. That is they lie to the left and right of the peak. Many that fall to the left, including the five most left points, are energy networks. These types of networks tend to focus more on redundancy to prevent outages. Meanwhile, two of the three networks that fall to the right of the peak are material networks that are centered around industry. These types of networks tend to focus on efficiency to maximize profit.

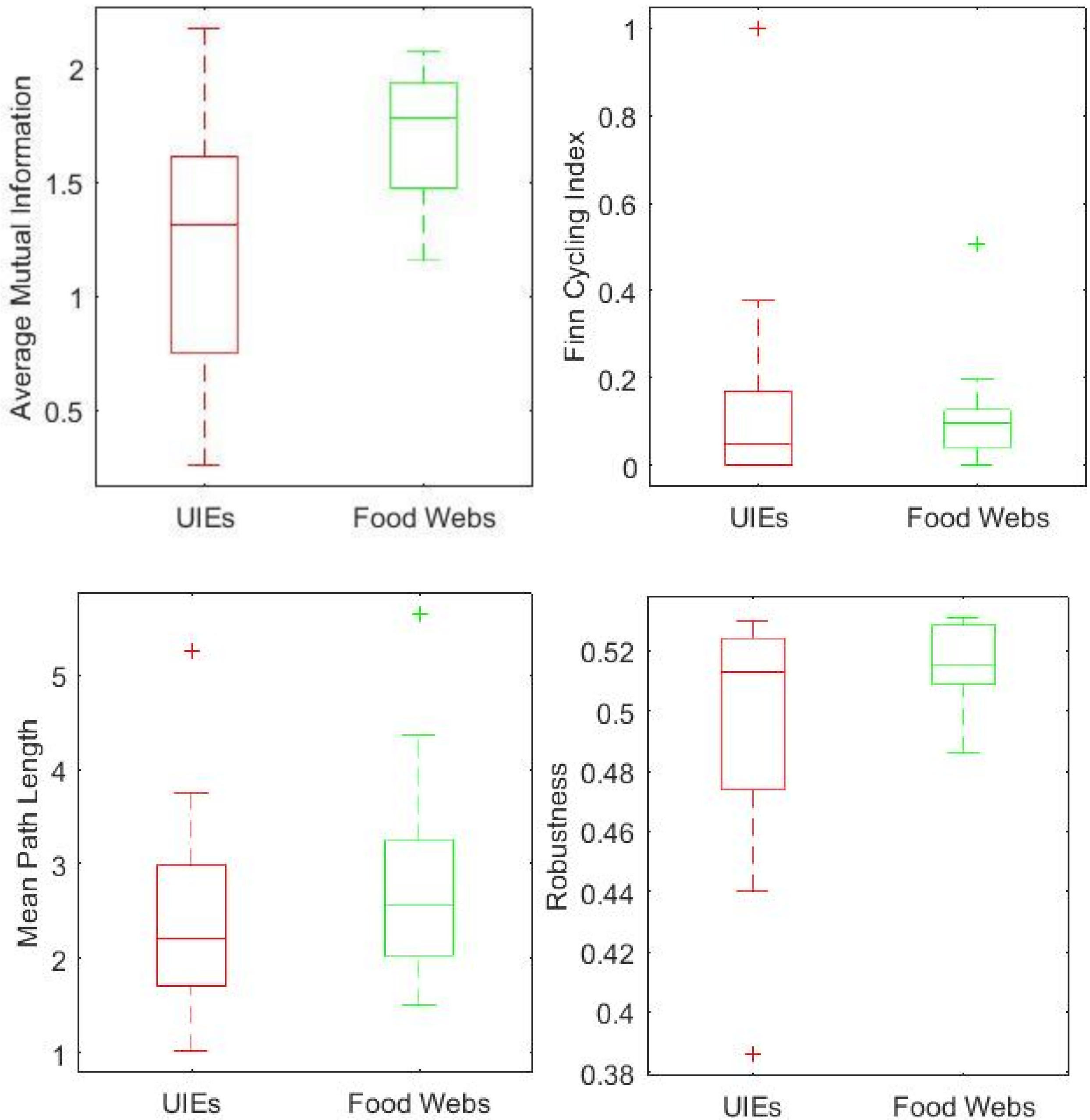


Figure 7 Comparison of Average Mutual Information (top left), Finn Cycling Index (top right), Mean Path Length (bottom left), and Robustness (bottom right) between Urban-Industrial Ecosystems and Food Webs

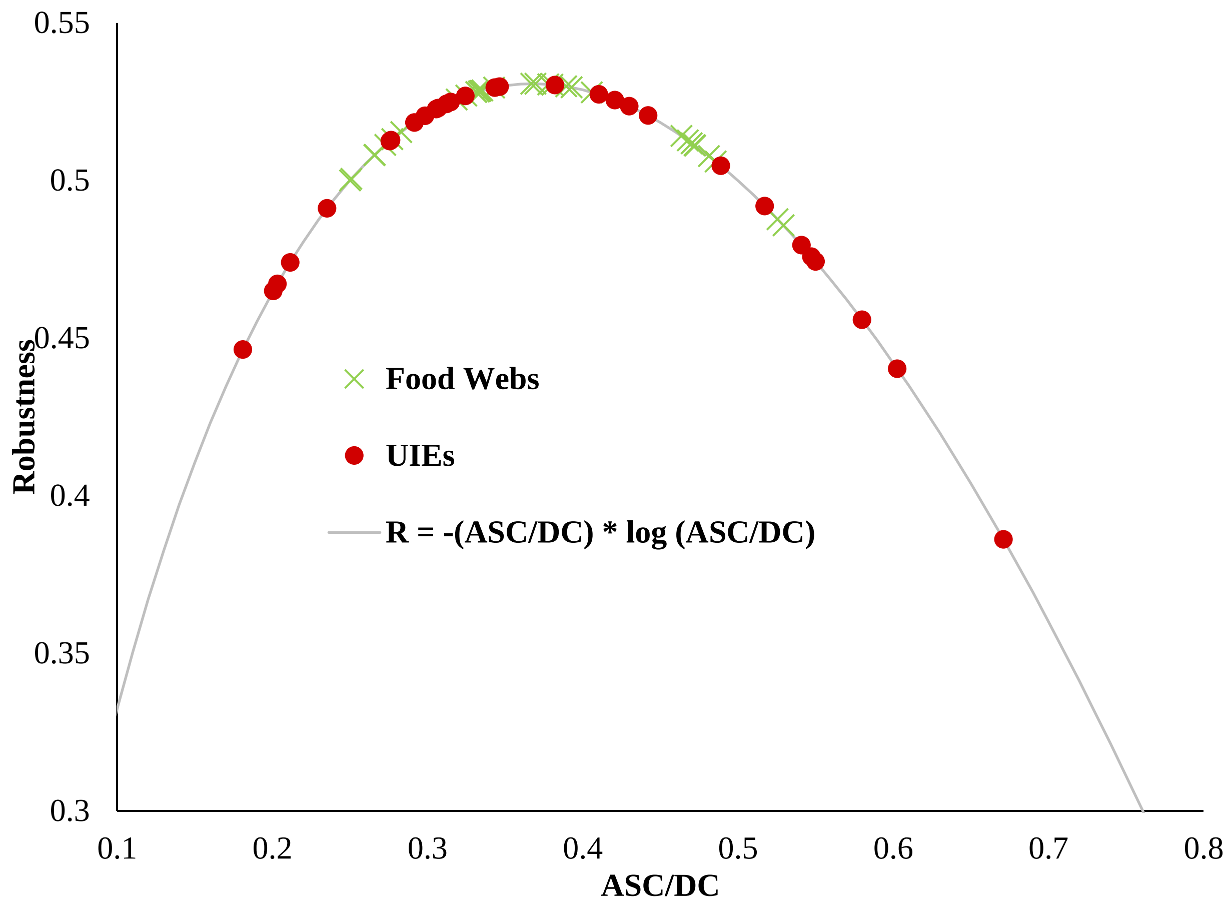


Figure 8 Robustness curve for Urban-Industrial Ecosystems and Food Wed datasets

Table 4 shows the results for the two new flow-based metrics. As shown, the Food Webs have a smaller Normalized Standard Deviation of AMI than the UIEs indicating there is a more equitable contribution of AMI among the actors in these systems. Also, the Food Webs have a lower percentage of actors that rely on a single source when imports are included. Comparing the Single Source Percentage results to the Specialized Predator Fraction, one sees that these values are larger, with the Food Webs average 13% more actors that are single source reliant compared with just being a specialized predator. There is about a 7% increase for the UIEs.

Table 4 Average values for two additional flow-based metrics for Food Web and UIE datasets

	Normalized Standard Deviation of AMI	Single Source Percentage
Food Webs	0.046	21.52%
UIEs	0.109	49.47%

4.3.3 Analysis of specific actor and network types

The type of actors present in UIEs strongly influence resulting network properties, shown in Table 5. Average Cyclicity and Finn Cycling Index values for the UIEs that include industry, agriculture, and the natural environment are higher than those values that do not include those actors. The most significant gap between Cyclicity values is that between the networks with and without agriculture, while the largest gap for Finn Cycling Index is the networks with and without a natural environment actor. Conversely, the networks that do not include a utility actor have higher cycling metrics than those that include a utility actor, with the difference in the Finn Cycling Index being quite a bit greater than the difference in cyclicity. Amongst all of the groupings, the networks without a utility actor have the highest average of Finn Cycling Index with a value of 0.318, and the networks that include an agriculture actor have the highest average of Cyclicity with a value of 2.492. As shown, the exact same trend is present with Linkage Density and Mean Path Length as the cycling metrics. These two metrics are not directly related, but both are generally a measure of the level of connection within a network The average value for

Linkage Density and Mean Path Length is greater for the networks with industry, agriculture, or natural environment actor types than those that do not include those actor types. Also, the average value for these metrics is lower in the networks that include a utility actor than those that do not. While the trend is the same, the difference in values are lower relatively, especially in the case of Mean Path Length.

Table 5 Average ecological metrics for UIEs that do or do not include specific actor types

	Cyclicity	FCI	Linkage Density	MPL
Includes Industry	1.885	0.234	2.279	2.432
No Industry	1.338	0.059	1.429	2.303
Includes Agriculture	2.492	0.299	2.717	2.423
No Agriculture	0.844	0.059	1.282	2.372
Includes Natural Environment	2.054	0.311	2.240	2.639
No Natural Environment	1.431	0.064	1.895	2.160
Includes Utility	1.280	0.014	1.940	1.808
No Utility	2.087	0.318	2.168	2.843

Similar to actor type, flow type has a strong influence on ENA values for the UIEs, shown in Table 6. The categories used are nutrients, energy, emergy, and material. This is smaller than the list from Table 1 as Nitrogen, Phosphorus, and Carbon are combined into one category labeled nutrients. The energy networks have the lowest value for Finn Cycling Index with a value of 0.006 and the emergy networks have the highest value with a value of 1.000. The energy networks also have the lower value for Average Mutual Information and the ratio of Ascendency to Development Capacity, while the material networks have the highest value for both of these metrics. The values for Robustness range between 0.462 and 0.512 with the nutrient networks have the highest value and the material networks having the lowest value.

Table 6 Average values for select ecological metrics for UIEs categorized by flow type

	FCI	AMI	ASC/DC	Robustness
Nutrients	0.047	1.533	0.413	0.512
Energy	0.006	0.708	0.235	0.486
Emergy	1.000	0.729	0.339	0.496
Material	0.206	1.656	0.511	0.462

One potential concern that arises from this analysis is co-variance between the actor types and the type of flow. Table 7 shows the breakdown of the inclusion or exclusion of a certain actor type and how many of the flow type networks fall into that category. As shown for many of the categories, only two or three network types are represented (e.g. only nutrient and emergy networks are including in the 15 networks that include a natural environment actor type). This is most concerning for the 7 networks that do not include an industrial actor as all of them are nutrient networks. Not all networks are represented in all categories, suggesting some ambiguity regarding the role of network vs. actor type in determining network properties.

Nutrient networks are represented in all of the actor type categories and provide a way to determine the contribution of actor type. The EIP dataset was added to the entire UIE data set for the structural metrics to have a larger sample and less potential for co-variance. Of the 48 EIPs, all (100%) included industry, 24 (50%) included agriculture, 6 (13%) included the natural environment, and 35 (73%) included utility. The total data set comprised 77 human designed networks categorized by actor type. This analysis yielded same results shown previously; the inclusion of industry, agriculture, and natural environment actor types had a positive impact on the ecological metrics, while the inclusion of a utility actor type had a negative effect on the metrics. Table 8 shows that for all but the FCI, the positive or negative effects remain the same as those shown in Table 5. Therefore, although there is some co-variance between the actor types included and the type of flow in the network, this does not the skew the results of the actor type analysis.

Table 7 Number of networks of specific network type that do or do not include actor types industry, agriculture, natural environment, and utility

	Network Type			
Includes	*Nutrient*	*Energy*	*Emergy*	*Material*
Industry	8	6	4	4
Agriculture	10	1	4	1
Natural Environment	11	0	4	0
Utility	5	6	0	1
Does not Include	*Nutrient*	*Energy*	*Emergy*	*Material*
Industry	7	0	0	0
Agriculture	5	5	0	3
Natural Environment	4	6	0	4
Utility	10	0	4	3

Table 8 Average structural ecological metrics for UIE and EIP data set that do or do not include specific actor types and average structural and flow ecological metrics for nutrient UIEs that do or do not include specific actor types

	With EIPs		Without EIPs, Only Nutrient Networks			
	Cyclicity	**Linkage Density**	**Cyclicity**	**Linkage Density**	**FCI**	**MPL**
Includes Industry	1.682	1.843	2.055	2.576	0.036	2.609
No Industry	1.338	1.429	1.338	1.429	0.059	2.303
Includes Agriculture	2.010	2.108	2.148	2.503	0.066	2.614
No Agriculture	1.262	1.479	0.865	1.116	0.009	2.169
Includes Natural Environment	2.014	2.148	1.984	2.217	0.055	2.599
No Natural Environment	1.514	1.677	0.750	1.250	0.011	1.871
Includes Utility	1.535	1.736	0.265	1.449	0.000	2.218
No Utility	1.832	1.915	2.448	2.336	0.070	2.590

4.4 Discussion

The results of the Ecological Network Analysis of the collected Urban-Industrial Ecosystems affirm previous research showing how these systems perform relatively similar to human designed systems (EIPs) and relatively worse than natural systems (Food Webs). Additionally, the results highlight the improved performance when specific actor functional roles are included such as industrial, agricultural, and natural environment actor types. The results of the flow type analysis show how the characteristics of these systems differ such as the amount of cycling present and the built in redundancy and/or efficiency. These insights further the understanding of how urban areas function and where there is potential for improvement.

4.4.1 Urban-Industrial Ecosystem comparative performance to other systems

The first major observation from the results is the generally similar performance between the various human designed systems despite differences in the flow substance. As shown, the UIEs and EIPs are very similar across all of the structural metrics. These networks are often of equal size (an average of 8 actors for UIEs vs an average of 12 actors for EIPs) with similar amounts of cycling and connectivity. Given the dataset of 48 EIPs and 29 UIEs, the data suggest human networks currently function similarly across regions and industries. This fairly robust dataset points to a certain threshold and range of performance for human designed systems as currently constructed. The metric where these two appear to differ the most is in the Percentage of Connecting Actors. There is a fairly large gap between the UIEs at 33% and the EIPs at 51%. This, and some of the other minor differences in results, is likely due to the differences in network construction. The EIPs are solely structural networks while the UIEs are flow networks. Therefore, the UIEs must contain a common currency throughout the system, while the EIPs do not, even in the pure structural analysis. This means the EIPs can have a multitude of different resources represented by a flow and are more likely to have actors that connect other actors because the resource does not have to remain consistent across that connection. For example, energy could flow from a power plant to water treatment facility which then sends water to a specific factory. That water treatment facility would act as a connecting node, even though the flow changes. This may also explain the presence of multiple SCCs in the EIPs. There are a greater number of these systems that have more than a single SCC compared with the UIEs. Having multiple resources represented in the network means these resources may stay within their own loop that is not connected to the other loops on the system.

The second major observation is how human systems consistently show poorer performance compared with natural ecosystems. This is glaringly true for the structural metrics of Cyclicity and Linkage Density as seen in Figure 6, as well as the additional metrics shown in Table 2. These structural features are key to determining the flow-based properties. In regard to the flow metrics, the UIEs are closer in performance to the Food Webs, but both cycling and path length are lower in these human systems than in their natural counterparts. There is a much greater reliance on single sources in the human-designed systems as well as the actors being less equitably distributed. This indicates there is still a large potential to increase the performance of these systems to match that of the natural systems. This is made most clear in the cycling metrics of these systems. Seventeen of the 77 UIEs and EIPs include a single cycle or no cycles at all with a much smaller fraction of the flow being cycled when compared with the Food Webs. Additionally, there are fewer actors that are involved in cycling for the human-designed systems with these cycles being much smaller. As mentioned in Section 3.2, the natural systems are much more limited in the resources they have access to because they are limited geographically. This means these systems must cycle the materials that are available, or they would deplete all resources. On the other hand, the human-designed systems have greater access to outside resources and therefore are not as concerned or reliant on the cycling of resources. They have greater access to supplement what is only geographically available.

Analysis of robustness indicates that human systems are sometimes overly redundant (left of the peak) or overly constrained (to the right of the peak) relative to the robustness of ecological systems. While 18 of the UIEs occupy the peak range characteristic of food webs, 11 do not with 5 on the left side and 6 on the right side. There is not a clear trend as to where the UIEs fall, but the larger spread indicates these systems are not as optimized for finding the balance between redundancy and efficiency when compared with the Food Webs. This points to some of the differences between these systems as mentioned in Section 3.2. Some human designed systems are planned around redundancy, while others are planned around efficiency. The natural systems are not planned at all and will occupy the balance between those two characteristics that is most optimal for the system.

4.4.2 Effect of actors and flow type in UIE performance

The groupings by inclusion of actor type show the influence that actor type has on the system under certain circumstances. Industry, agriculture, and natural environment actor types all have a positive effect on the ecological metrics. As mentioned previously, all of these act in a primary producer role, consuming raw material to output something useful to the system mimicking the lowest trophic level in a natural ecosystem. This is seen as the most critical part of natural systems due to the ability to process waste material into useful nutrients for other organisms. This is shown by examining two of the nitrogen networks in this dataset. The first network, a nitrogen network for the Central Arizona-Phoenix ecosystem (Baker et al. 2001), includes both agricultural actors (crops and dairies) and the natural environment (desert and near-surface atmosphere). This network has a Cyclicity value of 2.52 and an FCI of 0.182. The other network, a nitrogen network for Toronto (Forkes 2007), does not include an agricultural or natural environment actor. This network has a Cyclicity value of 1.00 and FCI of 0.002. In the Central Arizona-Phoenix network, these actors process outputs from wastewater and the urban landscape, cycling them back into the system as well as providing nitrogen to other actors. These being excluded from the Toronto network limit its ability to process the waste nitrogen as well as provide nitrogen, thus limiting the cycling. Industry is also able to process that material albeit with a much greater reliance on outside resources such as water and energy. This would indicate that an ideal UIE would include at least one of these actor types to best process flow and increase ecological performance. Alternately, networks that include a utility actor and consistently have a lower performance when compared to those that do not. This is also expected due to the linear nature of most utilities. They are often one time use resources where the input is used by a single actor before being expelled from the system. The centralized nature of utilities means there is seldom any cycling, as shown by the lower cycling metrics, and there is very little sharing between actors, as shown by the lower values for Linkage Density and Mean Path Length. This means the resources are not fully utilized, and there is potential to increase that utilization. However, this does not mean that utility actors should not be included in these systems, it simply highlights the need to improve these systems with a focus on this actor type. This could be done through the addition of technologies that recycle or upcycle this material and energy such as increased wastewater treatment, landfill gas recovery, and waste heat recovery. While not examined here, further research can be done on not just the presence of these actor types, but the amount of throughflow that these actors process. This would provide a greater perspective of how these actors influence the system.

The different flow type networks vary in ecological performance. As mentioned, the energy networks have very low value for FCI indicating virtually no cycling in these systems. This is expected as energy is not easily cycled with most energy usage eventually being dissipated as heat. Four of the 6 energy networks studied included at least one cycle through the use of technologies such as electricity generation from the incineration of solid waste. However, the relative amount of this cycled energy compared with the total usage was incredibly small leading to the extremely low values for FCI. This link between structure and flow for cycling is not always apparent, and thus it is critical to analyze both to truly understand the system. This low cycling result matches with the networks that include a utility actor as most often that utility is an energy provider. Interestingly, the emergy networks have an FCI of 1 meaning all of the flow is being cycled within these networks. However, this is due to the fact that all of these networks come from the same source and each one is only a 3 actor network that is fully connected (every actor sends and receives flow to every other actors).

Analysis of AMI indicates that the material networks are the most constrained networks with the energy networks being the least constrained. The material networks have high AMI, as might be expected given that most materials are specific to certain industries and are not easily expanded beyond that specific purpose. The energy result is surprising given what has been previously mentioned about the linear nature of energy utilities. In these systems, there is often a single path that a flow can take from import to export, so it is interesting to find that the flow in these networks would be the least constrained compared with the other flow networks. This could be explained by the redundancy built into these networks. With an ASC to DC ratio of 0.235 this indicates a network that is more redundant than it is efficient. Energy utilities are a critical infrastructure so there is a desire to design these systems as more redundant leading to lower Robustness. In contrast, nutrient networks have a much higher value for Robustness. Considering the nutrient networks consist of Nitrogen, Phosphorous, and Carbon flows there are a number of natural processes (e.g. nitrogen and carbon cycles) that are occurring within these systems, independent of the city or industrial interactions. This means they more naturally align with the natural systems as they include some of those same processes and thus have the closest value to the Food Web median Robustness of 0.524. If nature is the benchmark, the networks that contain similar processes will likely get closest to that benchmark.

4.4.3 Qualitative observations for the gap in performance

As shown, there is a large gap in quantitative ecological performance between the human designed systems and natural ones, which may reflect multiple factors and further highlight the differences shown in Section 3.2. The first is that types of cycles that exist within these systems. In the human designed systems, the cycles present are often only between two actors. An example of this would be waste paper being sent from one actor to the paper manufacturer to be recycled, that is then sent back to the original actor as shown in a timber manufacturing system in the Swiss lowlands (Hendriks et al. 2000). These two-actor cycles inflate the Cyclicity metric without adding much more utility to the system as a whole. Conversely, cycles within the natural systems have much longer path lengths starting from plant actors through many trophic levels before ultimately ending in up in detrital actors that feed back into the plants. This difference in cyclic path length could be one of the major factors in relatively poor performance of human systems. Moreover, the functional differences between actors participating in cycles has a major effect. Detritus actors process a large majority of all material and energy within natural ecosystems making them essential for cycling (Townsend, Begon, and Harper 2003). These actors take in the "waste" from the system and process it to be useful again, participating in many cyclic pathways. Detrital-type actors within EIPs also increase cycling performance (Layton et al. 2016b). Within the UIEs examined in this study, the waste processes (such as landfills and wastewater treatment plants) are huge sinks of resources that do not cycle back into the system, but rather export materials once they have been processed. This lack of connection back to the system is another big difference between the human systems and natural ones that could explain some of the gap in ecological metrics. These two observations require further quantitative analysis and should be investigated in future work.

An important consideration is the level of aggregation within each network, or in other words how specific (or nonspecific) the actors are involved. In general, the smaller networks had a greater level of aggregation with more nonspecific actors when compared with the larger networks. For example, in some networks an actor may be labeled "industry" instead of listing out the specific industries that were encompassed in that term while in others those specific industries are separated. Although the level of aggregation cannot be quantified due to the variance between the networks, it is an important qualitative measure to be aware of while analyzing and comparing this dataset. This is an ongoing area of research and hopefully something that can be understood more in future work.

4.5 Conclusions

As shown, Ecological Network Analysis can be used to analyze urban and industrial networks. This study reinforces previous findings that human designed systems lack in ecological performance when compared with natural systems. Given the inherently sustainable nature of ecosystems, these metrics can help guide the creation and adaptation of Urban-Industrial Ecosystems towards greater sustainability. Some key areas to improve system performance are to include industrial, agricultural or natural actors that provide greater ecological performance and increased recycling. Additionally, there should be a focus on waste processors as these are the most critical actors in natural systems. Data availability will continue to be an issue when modeling these systems, but well defined networks with greater granularity and robust flow data will give the best picture of how these systems currently operate and of potential limiting factors.

CHAPTER 5. IDENTIFYING KEY ACTORS USING SYSTEM WIDE ECOLOGICAL METRICS

As stated previously, ENA is a wide ranging form of analysis that has been developed over many years. As such, there are many different metrics that have been created for different types of analysis. In addition to the metrics used in the previous chapters, there are metrics that look at trophic levels, path lengths, modularity, heatedness, taxonomic groups, stability, and the impact of species removal (Lau et al. 2017). This chapter examines four additional ENA metrics that seem especially relevant, and uses them to analyze the Food Web, EIP, and UIE data sets. These additional metrics extend beyond the single value metrics defined in Chapter 3 and 4 to metrics that generate data for each actor and pairwise interaction. This more robust analysis of specific interactions allows for key actors and exchanges to be identified. Additionally, some overall network characteristics are able to be identified such as the network mutualism that takes into account the number of positive and negative interactions. Overall, this chapter complements and deepens the analysis previously shown allowing for further conclusions to be drawn about the human-engineered and natural systems.

5.1 Additional Analysis Defined

The additional analyses there were selected are Centrality, Utility, Mixed Trophic Impact, and Control/Dependence Analysis. Each of these provides a different look into the network interactions at an aggregated and actor by actor level. This section defines each of these metrics, how they are calculated and provides some examples of where they have been used in previous ecological and human-designed systems.

5.1.1 Centrality

Centrality is a concept in graph theory for measuring the degree to which a node is well connected and influential to a network. It was first developed around social networks to understand influence and communication (Freeman 1978). It can be used as a relative ranking of nodes based upon their positional importance in the system. The concept of centrality has been used in many applications including social networks, diffusion of technological innovation, and organizational structure (Freeman 1978). There have also been numerous applications to ecology. Centrality was used to understand landscape connectivity in regards to the movement and dispersal of organisms within that region (Estrada and Bodin 2008). It has also been used in studying Food Webs to identify key species within an ecosystem (Cagua, Wootton, and Stouffer 2019; Estrada 2007; Jordán, Liu, and Davis 2006; Martín González, Dalsgaard, and Olesen 2010). There are many different centrality indices that indicate specific network characteristics. For this study, the focus will be on Degree Centrality, Betweenness Centrality, Closeness Centrality, and Eigenvector Centrality.

Degree Centrality is the simplest Centrality index. The degree of a node is the number of nodes with which it is connected (Freeman 1978). The higher the degree, the more connected the node is to others. This can be both indegree and outdegree quantifying the number of nodes that point towards a node or the number that a node points towards, respectively. This is defined by

$$C_D(i) = k_i \tag{26}$$

where i is the node of interest and k are the number of links to or from that node.

Beyond the individual node, it is important to understand pathways of multiple nodes. A point is considered to be central if it falls between other points along the shortest path. This middle point is important because of its influence on the communication between the two nodes that are not directly connected. This is measured by the index *Betweenness Centrality* (Freeman 1977). This can be calculated for each point by finding the probability that a random shortest path between two nodes will contain the middle point in question, and summing those probabilities to find that middle point's betweenness. This is defined by

$$C_B(i) = 2 \times \sum_{j<k;i\neq j} \frac{\frac{g_{jk}(i)}{g_{jk}}}{(n-1)(n-2)} \tag{27}$$

where g_{jk} is the number of paths between j and k and $g_{jk}(i)$ is the number of those paths that include i.

Closeness Centrality is a measure of proximity of the node of interest to all other nodes in the network. A node is closest when it directly touches another node. A node that is one length away from all other nodes will have a Closeness Centrality of 1, the maximum value possible. This centrality measures the ability of a node to influence all other nodes (Freeman 1978). This is calculated by looking at the shortest path lengths between nodes. It is defined by

$$C_C(i) = \sum_{j\neq i} \frac{n-1}{d_{ji}} \tag{28}$$

where d_{ji} is the shortest path length between i and j and n is the number of nodes.

Eigenvector Centrality is a measure of the influence each node has over all other nodes. Each node is assigned a value based on the level of connection in addition to the nodes with which it shares a connection. Those nodes that are well connected in addition to be other well connected nodes will have a higher value for Eigenvector Centrality. The summation of all values for this centrality is always 1, allowing easy comparison across networks regardless of size or level of connection (Bonacich 1987). This is defined by

$$C_E(i) = \frac{1}{\lambda} \sum_j \boldsymbol{A}_{ij} C_E(j) \tag{29}$$

where $\mathbf{A}_{ij}$ is the adjacency matrix and λ is the maximum eigenvalue of that matrix.

Estrada analyzed 17 food webs using six centrality measures (the four shown here plus an additional two), noting the how they differed by scale. Degree and Betweenness Centrality were shown to focus more on local interactions, while Closeness and Eigenvector Centrality were more focused on global interactions. Additionally, there was a strong correlation between the centrality measures in some of these food webs, while in others there was not. This shows there is some difference in the indices, but also highlights the unique perspective that each one brings (Estrada 2007). Another study analyzed the Chesapeake Bay trophic flow network with 13 network indices including Degree, Closeness, and Betweenness Centrality to understand how each ranked species importance. Degree Centrality is useful for a quick analysis, whereas Betweenness and Closeness would be useful when wanting to understand how a specific species transmits effects (Jordán et al. 2006). An analysis of 34 pollinator networks was conducted using Closeness and Betweenness Centrality. For these geographically small networks, almost all of the species have a high value for Closeness, while roughly 40% of them act as connector species with high values for Betweenness. These generalist species are key to connecting subsets of these networks and Betweenness is one way to identify them (Martín González et al. 2010). Overall, these centrality indices each provide a different perspective into the relative importance of the components of a network, and it is important to include each in analysis.

5.1.2 Utility Analysis

Utility Analysis in Ecological Network Analysis is a way of describing the positive and negative interactions within a system. Positive utility occurs when one actor receives energy or nutrients, while negative utility is when one actor loses energy or nutrients, and are expressed relative to the total flow through the node of interest. This utility can be analyzed for both direct and indirect interactions giving both an overall view of the network synergy (or lack thereof), as well as understanding the relations between individual components. This provides analysis for both the top-down (consumer controlled) and bottom-up (producer controlled) processes that occur within a system (Fath and Patten 1998).

The matrix of direct utility can be calculated by

$$d_{ij} = \frac{f_{ij} - f_{ji}}{T_i} \tag{30}$$

where d_{ij} is the matrix component i,j or the direct utility matrix D, f_{ij} is the flow from component j to component i, f_{ji} is the flow from component i to component j, and T_i is the total inflow into the node i. In this analysis, the numeric value of this interaction is not of consequence, but rather the sign of the value being calculated whether that be positive, negative, or neutral. Therefore, this matrix is modified by

$$sgn(D) \tag{31}$$

to understand the utility interactions. Indirect interactions are calculated using the higher powers of the direct utility matrix to assess effects of longer pathlengths within the network. These higher powers can be simplified into a power series to calculate the overall indirect matrix. The integral utility matrix which calculates the indirect flows is given by

$$U = (I - D)^{-1} \tag{32}$$

where U is the integral utility matrix and I is the identity matrix. As before, the values of this matrix are of less interest than the signs of the components. The total can be summed. If this sees more positive than negative interactions, the network is said to exhibit mutualism if the total number of positive interactions exceeds the negative relationships, while the network exhibits antagonism if there are more negative interactions. However, it has been stated that ecosystems will almost always exhibit mutualism and very rarely exhibit antagonism. In particular a network configuration in which all compartments are "solely dependent on the same single resources is probably not stable, and therefore, unlikely to occur in natural ecological networks" (Fath 2007).

Beyond the overall sum of signs, the pairs that are created between components also describe important relationships. These can be categorized based upon the pair-wise sign values as follows: mutualism (+,+), competition (-,-), exploitation (+,-), exploited (-,+), neutralism (0,0), commensalism (+,0), amensal host (-,0), commensal host (0,+), and amensalism (0,-). These relationships exist for both the direct and indirect interactions. Additionally, the mutualism ratio (also known as mutualism index) can be calculated for the entire network by looking at the ratio of positive interactions to negative links (Fath 2007).

Zhang et al. conducted a study of urban energy metabolic systems around 4 different Chinese cities: Beijing, Tianjin, Shanghai, and Chongqing. They found all 4 cities had a mutualism index of below 1 ranging from 0.29 to 0.74. Additionally, there were more exploitation relationships than any other kind of relationship for all 4 cities, followed by competition, and mutualism relationships were fewest (Zhang, Yang, Fath, et al. 2010). These same researchers also examined the urban water metabolic system for Beijing over 5 years finding that the system exhibited overall mutualism (mutualism index >1) in all years. Additionally, they identified interactions between specific components and relationships that changed over time (Zhang, Yang, and Fath 2010). Other studies also used Utility Analysis for various human-designed systems of energy, water, economic, and power generation network, and these studies frequently used other aspects of ENA as well (Briese et al. 2019; Lu et al. 2015; Peng et al. 2019; Tan et al. 2018; Yang et al. 2014; Yang and Chen 2016; Zhai et al. 2019; Zhang et al. 2014, 2009; Zheng et al. 2019). Many of these studies characterize the mutualism relationships as beneficial and the competition and exploiting relationships as negative. Additionally, some of these studies look over multiple years to understand how the relationships between actors changes over that time frame.

5.1.3 Control/Dependence Analysis

Control/Dependence Analysis is derived from traditional control theory. Control is defined by "the extent or degree to which elements influence each other and contribute to the system's overall flow-storage pattern" (Fath 2004). This is calculated by analyzing the input and output environs of each component of the network. The first step is to calculate the generating transfer efficiencies given by

$$g_{ij} = \frac{f_{ij}}{T_j} \tag{33}$$

and the receiving transfer efficiencies given by

$$g'_{ij} = \frac{f_{ij}}{T_i} \tag{34}$$

These are then used to calculate the integral flow matrices given by

$$N = (I - G)^{-1} \tag{35}$$

$$N' = (I - G')^{-1} \tag{36}$$

similar to integral utility matrix shown previously. Finally the calculations for the control and dependence matrices are given by

$$CA = \left[ca_{ij}\right] = \begin{cases} n_{ij} - n'_{ji} > 0, ca_{ij} = \dfrac{n_{ij} - n'_{ji}}{\sum_{i=1}^{m} n_{ij} - n'_{ji}} \\ n_{ij} - n'_{ji} \leq 0, ca_{ij} = 0 \end{cases} \tag{37}$$

And

$$DA = \left[da_{ij}\right] = \begin{cases} n_{ij} - n'_{ji} > 0, da_{ij} = \dfrac{n_{ij} - n'_{ji}}{\sum_{j=1}^{m} n_{ij} - n'_{ji}} \\ n_{ij} - n'_{ji} \leq 0, da_{ij} = 0 \end{cases} \tag{38}$$

This control allocation (CA) matrix examines “the difference of two pair-wise integral flows normalized by…the component that controls the other component” (Chen, Fath, and Chen 2011). In other words, this describes how consumers control producers. Conversely, the dependence allocation (DA) matrix examines the other side of this by quantifying how consumers are dependent on producers (Chen and Chen 2015). This analysis can identify those key actors that either exhibit a large amount of control over individual components or the network as a whole, as well as those actors with which many other actors are dependent. An analysis of urban energy consumption was able to identify the control and dependence of different sectors within the urban landscape. Manufacturing and services were identified as being two of the dominant components driving energy consumption due to the fact that all other components were highly dependent on them (Chen and Chen 2015). An analysis of solar photovoltaic power generation systems also used this control allocation to show the large control dissipated energy had over all other components (Briese et al. 2019). Additional studies have Control Analysis this to analyze the energy-water nexus (Chen and Chen 2016; Yang and Chen 2016), economic networks (Tan et al. 2018), the energy-metal nexus (Peng et al. 2019), and a carbon network for an EIP (Lu et al. 2015).

5.1.4 Mixed Trophic Impact

Mixed Trophic Impact analysis is a way of computing the cumulative effects of ecosystem interactions between actors in the system. It is a way of measuring the effects of the change in biomass of one actor on all other actors in the system (Hannon and Joiris 1989; Ulanowicz and Puccia 1990). Similar to Utility Analysis and Control/Dependence Analysis, this takes into account the direct and indirect flows, looking at pathways of all lengths to calculate impact. This calculation is very similar to the other types of analysis as well. The impact between actors is calculated looking at the fraction of a predator’s diet is comprised of each prey as well as the fraction of a prey’s net output (ignoring losses due to respiration) is consumed by each predator (Ulanowicz and Puccia 1990). These two fractions are defined by

$$d_{ij} = \frac{T_{ij}}{\sum_k T_{kj}} \tag{39}$$

And

$$h_{ij} = \frac{T_{ij}}{\sum_m T_{im}} \tag{40}$$

where T_{ij} is the amount of prey i consumed by predator j. Using these two, the direct net impact can be calculated with

$$q_{ij} = d_{ij} - h_{ji} \tag{41}$$

Finally, taking into account all pathway lengths and indirect effects, the total mixed trophic impact matrix is calculated by

$$M = (I - Q)^{-1} - I \tag{42}$$

This differs from Utility Analysis in that both the sign and value of each component is of importance. The value describes how much impact (whether positive or negative) one actor exhibits in relation to all other actors.

5.2 Results

The large number of actors in some of the systems (especially the natural food webs), suggest it is useful to first look more broadly at the data to identify overall trends. This is done to highlight the actor types that consistently have the greatest influence across all systems. Since the networks are varied, the specific actors that are identified as critical are not as important as their general type and function (i.e. producer, consumer, recycler, etc.). The main purpose of this analysis is to identify which functions are most critical in these systems based off these metrics. This is done for all of the networks. Additionally, a more detailed approach examining some of the individual links and actors is conducted for a single network to understand how exactly those interactions work and how they influence the network as a whole. Ideally, this would be done for all networks, but it is not possible to perform that detailed analysis in this dissertation given there are over 600 links among the 29 UIEs and close to 18,000 links for the 31 natural systems. As with the previous metrics, the goal is to gain understanding of how these networks work and how that understanding can be applied to all networks in the form of sustainable design guidelines which come in the next chapter. All results shown include all 29 UIEs and all 31 Food Webs.

5.2.1 Centrality

For each Centrality index, there is a resultant value for each actor in a network. This is shown for an example network in Table 9. This was performed for all Food Webs, UIEs, and EIPs. To understand how the centrality measures were related, the Spearman rank order correlation was calculated between each pair of Centrality indices for all networks. These correlations were then averaged based on dataset with the results shown in Table 10. The averages from this table only contain correlations that were statistically significant (p-value < 0.05). As shown, all of the correlations are greater than 0.5, with stronger correlations existing within the human-designed systems than the natural ones. The strongest correlation is between Degree and Closeness Centrality, while the weakest correlation is between Betweenness and Eigenvector Centrality.

Table 9 Centrality index results for each actor of Central Arizona Phoenix nitrogen network

	Betweenness	Degree	Closeness	Eigenvector
Desert	0	1	0.048	0.038
Near-surface atmosphere	20.83	5	0.077	0.144
Crops	21.33	5	0.071	0.166
Dairies	0	3	0.063	0.115
Humans	9.33	4	0.063	0.126
Pets	0	1	0.045	0.023
Wastewater	6.00	4	0.067	0.142
Urban landscapes	13.67	4	0.071	0.086
Subsurface	5.83	3	0.063	0.104
Landfills and Palo Verde	0	2	0.059	0.056

Table 10 Average Spearman rank order correlation values between pairs of Centrality indices for Food Webs, UIEs, and EIPs

Centrality Pair	Food Webs	UIEs	EIPs
Betweenness - Degree	0.661	0.786	0.830
Betweenness - Closeness	0.654	0.737	0.804
Betweenness - Eigenvector	0.549	0.686	0.772
Degree - Closeness	0.946	0.944	0.886
Degree - Eigenvector	0.860	0.892	0.883
Closeness - Eigenvector	0.838	0.853	0.899

Given these results, it was possible to aggregate the Centrality indices by ranking each actor base on the four indices and averaging those ranks together. All indices were given the same weight in that average. This gives the most central actor based off the number of connections, how well it connects other actors, how close it is to all other actors, and the influence it has. Table 11 shows an example of the centrality ranks for the Central Arizona Phoenix nitrogen network. In this example, two of the actors (near-surface atmosphere and crops) are consistently the top 2 ranked actors by all of the centrality indices. This network along with one ecosystem and one EIP is shown in Table 12. The top 3 (with ties) actors for each centrality as well as the averaged centrality ranks is shown for each of the networks. The Appendix in Table 53 and Table 54 shows these centrality rankings for all of the networks. In 24 of the 31 ecosystems, there is a unanimous top ranked actor across all centrality indices. In 24 of the 48 EIPs, there is a unanimous top ranked actor across all centrality indices. In 12 of the 29 UIEs, there is a unanimous top ranked actor across all centrality indices.

Table 11 Centrality ranks for actors in Central Arizona Phoenix nitrogen network

	Betweenness	Degree	Closeness	Eigenvector	Average
Desert	7	9	9	9	8.5
Near-surface atmosphere	2	1	1	2	1.5
Crops	1	1	2	1	1.25
Dairies	7	6	5	5	5.75
Humans	4	3	5	4	4
Pets	7	9	10	10	9
Wastewater	5	3	4	3	3.75
Urban landscapes	3	3	2	7	3.75
Subsurface	6	6	5	6	5.75
Landfills and Palo Verde	7	8	8	8	7.75

Ecological networks have mostly detritus, detritivores, and primary producers ranked for each centrality index. This includes particulate organic carbon, algae, shrimp, and plankton species. This is expected as these groups either consume or provide a lot of resources, and so are connected with many of the actors across the network; that is, they have a high Degree Centrality. They are not only well connected but help to connect other actors as shown by the high betweenness and closeness. Shown in Table 12 is one ecosystem in which the top ranked actor across all centrality indices is the sediment particulate organic carbon (detritus). The other two top ranked actors are detritivores. There are some instances where organisms in higher trophic levels are in the top ranked actors. Some examples include specific types of fish, sharks, snakes, and crabs. These larger organisms obviously have the ability to affect these ecosystems as they may feed on a number of the smaller organisms within it. Generally speaking, however, they are not the most critical functional groups as defined by these centrality measures that take into account the number and importance of interactions.

The central actors in the human-designed systems do not fall into a small subset of functional groups as compared with the ecological networks. As mentioned in Chapter 3, the human designed systems do not include easily distinguished trophic levels. There are no clear tiers of actors like those found in the natural ecosystems. The actors ranked at the top include utilities such as power plants and water supply, agriculture, specific industries such as a brewery, composting, landfills, and the atmosphere. There does not exist a clear central actor in the human-designed systems. This can be seen by examining two nitrogen networks. In the Central Arizona Phoenix nitrogen network (shown in Table 12), crops and the near-surface atmosphere are the two highest ranked actors based on centrality. In the Stockholm nitrogen network, the air and waste management are the two highest ranked. These two UIEs include many of the same actors, but the actors with highest Centrality differs between the two. In some cases, there is a recycling actor that is most central as is the case for the EIP listed in Table 12. This network is focused around food production and has many agricultural actors. Therefore, there is a lot of emphasis around the biodigestion which receives waste from many actors and provides fertilizer and biogas to other actors in the network.

The most central actor in these networks is greatly dependent on the type of network and where resources are focused. As mentioned previously, these networks are completely manmade with the exception of the natural environment they inhabit. Therefore, the designers determine what is going to be most central based upon what is included or excluded. These systems vary greatly, and as such the central actors appear to vary just a much. Even among similar networks, there is not a strong case to be made about a specific actor or actor type consistently being the most central. Therefore, this more general analysis is not useful in determining what is central to all human-design systems. It is more useful to look at specific networks to understand what is central to that particular network and how this is a critical piece of the system. It can also help identify actors that operate on the fringes of these networks.

Table 12 Centrality index ranks for one Food Web, one UIE, and one EIP

Sylt-Romo Bight									
	Betweenness		*Degree*		*Closeness*		*Eigenvector*	*Average*	*Average Rank*
1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
2	Corophium arenarium	2	Sediment bacteria	2	Crangon	2	Sediment bacteria	Crangon	3
3	Suspended Particulate Organic Carbon	2	Crangon	2	Nereis diversicolor	3	Crangon	Nereis diversicolor	4.25
Central Arizona Phoenix Nitrogen Network									
	Betweenness		*Degree*		*Closeness*		*Eigenvector*	*Average*	*Average Rank*
1	Crops	1	Crops	1	Near-surface atmosphere	1	Crops	Crops	1.25
2	Near-surface atmosphere	1	Near-surface atmosphere	2	Crops	2	Near-surface atmosphere	Near-surface atmosphere	1.5
3	Urban landscapes	3	3 tied	2	Urban landscapes	3	Wastewater	Urban landscapes	3.75
								Wastewater	3.75
GERIPA, Brazil									
	Betweenness		*Degree*		*Closeness*		*Eigenvector*	*Average*	*Average Rank*
1	Biodigestor	1	Biodigestor	1	Biodigestor	1	Biodigestor	Biodigestor	1
2	Cogeneration	2	Cogeneration	2	Cogeneration	2	Cogeneration	Cogeneration	2
3	Sugarcane farming	2	Alcohol production	2	Alcohol production	2	Alcohol production	Alcohol production	2.5

5.2.2 Utility Analysis

All Utility Analysis in these results are total Utility (Equation 32) which accounts for direct and indirect interactions within the systems. Table 13 shows the averaged Utility Analysis results for the UIEs and Food Webs. On average, the UIEs have a greater percentage (51.4%) of exploitative relationships than the Food Webs (45.3%), while the Food Webs have a greater percentage of mutualism relationships (18.3% vs. 10.8%). For the UIEs, there are more exploitative relationships than any other, followed by competition, neutral, and finally mutualism. For the Food Webs, there is similarly more exploitative relationships, followed by competition, mutualism, and finally neutral. Figure 9 shows the individual Utility relationship percentages for all of the UIEs and Food Webs, while Table 14 shows the variation (standard error) across the two datasets. As shown, there is less variance in these percentages for the Food Webs than for the UIEs. Additionally, all of the Food Webs have some mutualism relationships, while 7 of the UIEs do not include any of these relationships. The mutualism indices for all networks are shown in the Appendix in Tables 53 and 54. As shown, the average mutualism index for the UIEs is 1.22 while the average mutualism index for the Food Webs is 0.91. Additionally, 16 of the 29 UIEs (55.2%) have a mutualism index over 1 while 10 of the 31 Food Webs (32.3%) have a value over 1.

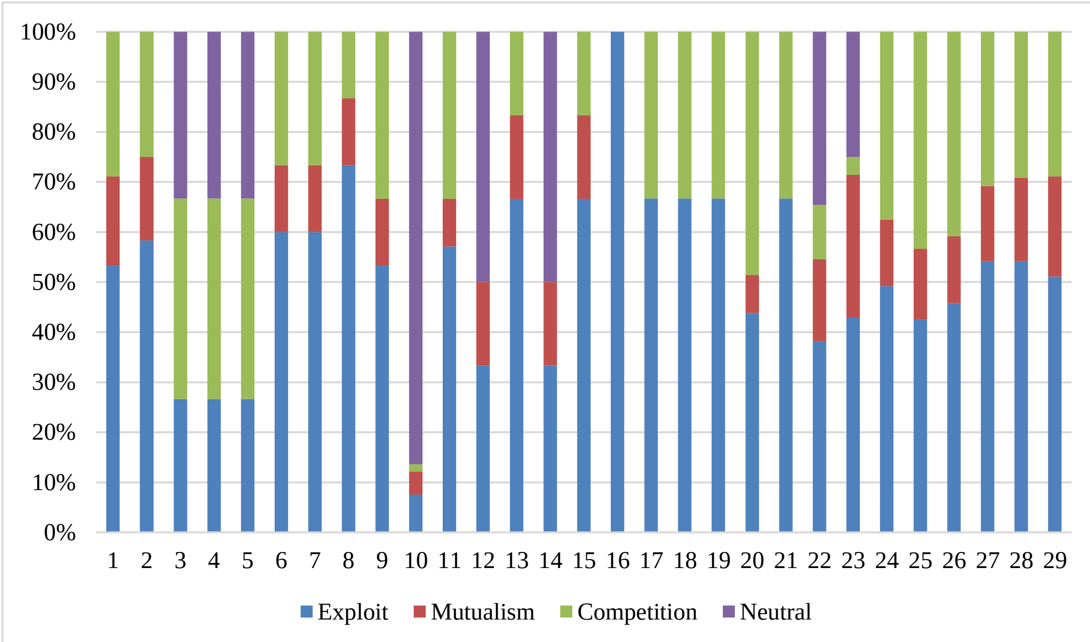
Table 13 Average percentage of Utility Analysis relationships for UIEs and Food Webs

	UIEs	Food Webs
Exploit	51.43%	45.33%
Mutualism	10.81%	18.28%
Competition	25.83%	26.51%
Neutral	11.93%	9.88%

Furthering the Utility Analysis, the top positive and negative contributors to utility were calculated. Similar to how the overall mutualism index can be calculated by looking at the total number of positive and negative interactions in the system, this can be done for each actor by summing all of the links between that actor and all other actors. Looking at the actors with the overall most positive and negative utility helps to identify the sources and sinks in the networks. The Appendix in Table 57 and Table 58shows the top 2 actors (with ties) for positive and negative utility for the UIEs and Food Webs, respectively. Those actors with a high positive utility are the main sources in these systems. They provide more resources than they take. Conversely, those actors with a high negative utility are the opposite and are the main sinks in these systems. They consume more resources than they provide.

Table 14 Variance of different Utility relationship types for UIEs and Food Webs

	Exploit	Mutualism	Competition	Neutral
UIEs	3.27%	1.42%	2.57%	3.93%
Food Webs	1.45%	0.97%	1.38%	2.93%



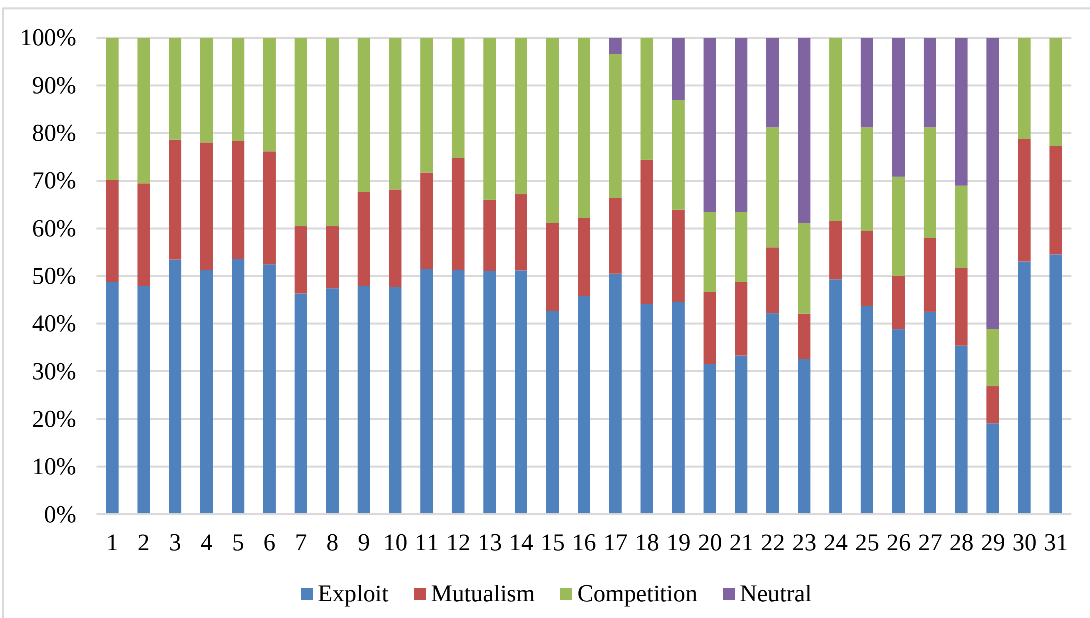


Figure 9 Individual Utility Analysis relationships for UIEs (top) and Food Webs (bottom)

This can be seen in the ecosystem data. The actors with the highest positive utility mostly include small organisms that make up the lower trophic levels of the system. This includes plankton, algae, bacteria, and other producers. These organisms are fed on by many organisms, but feed on very few if any other actors in the system. On the other side, the actors with the highest negative utility are mostly detritus or detritivore actors. These organisms take in a resources from many organisms, but are not fed on by many within the system.

Similar to the Centrality indices, the human-designed systems do not have as clear of a distinction for specific actor types that exhibit either high positive or negative utility. It is largely variant between networks. This can be used, however, to help identify the sources and sinks within these networks. For example, in the Central Arizona Phoenix Nitrogen network, crops have the highest positive utility, while the near-surface atmosphere has the higher negative utility. Crops are consumed by 4 actors which take a total of 34.4 Gg N while it consumes from 4 actors with a total of 21.5 Gg N. The near-surface atmosphere is consumed by 3 actors with a total of 22.2 Gg N while it consumes from 5 actors with a total of 57.2 Gg N. This does not take into account imports, exports, and dissipation that balances these actors to steady state.

Looking closer at this network, one can identify the specific pair-wise relationships. This can be done for all actors, but the humans actor is specifically highlighted here. Within this network, humans exploit the Desert, Crops, and Dairies actors. They are exploited by the Pets, Wastewater, and Landfills and Palo Verde actors. They exhibit mutualism relationships with the Near-surface atmosphere and Subsurface actors. They exhibit a competition relationship with the Urban Landscape actor. The humans tend to exploit those actors that have a resource to offer, which in the case of crops and dairies is food. As the human population increases, these actors will see a decrease as they are consumed in greater amounts. Conversely, the humans are exploited by actors that take in waste. Waste gathering actors “consume” waste generating actors and this shows up as exploitation in Utility Analysis. The mutualistic relationships can be explained that as human population goes up, there will be more nitrogen in these networks and therefore more nitrogen in the atmosphere and subsurface actors. Finally, the competition relationship is explained by both actors needing nitrogen and the limited resources make these two actors at odds. It is important to remember that this takes into account all direct and indirect effects. Although there is no direct interaction between humans and the Urban Landscape actor, the indirect effects along longer pathways puts these two in competition with one another. The origin of the nitrogen that is in competition for these two actors is imported directly into the Near-Surface Atmosphere and propagated either directly (in the case of the Urban Landscape) or indirectly (through pathways of Crops and Dairies for the Humans actor) to the two actors. This means they are drawing from the same source of nitrogen, even if they are not directly tied to one another.

5.2.3 Mixed Trophic Impact

As with Utility, all results here are for the total Mixed Trophic Impact (Equation 42) taking into account direct and indirect flows. The total impact for each actor was summed to generalize and aggregate the Mixed Trophic Impact (MTI). The real-world effect of this is examining the total biomass change that would occur in the system if the biomass of the actor of interest was increased. The impact on other actors can be either positive or negative, meaning summing opposing interactions could falsely imply a given actor has little impact. Thus, the absolute values were summed to see the collective impact of positive and negative effects. This is not an accurate representation of the change of total change in biomass but rather a representation of the amount of activity that would occur throughout the system given the change in a single actor. This largest cumulative absolute impact was used to identify the most impactful actor in the system.

The results for the MTI analysis are shown in Appendix in Table 59 and Table 60. This displays the most overall positive impact, most overall negative impact, and the most overall cumulative impact. Specifically examining the ecosystems, it is unsurprising to see similar results to the Utility Analysis. Many of the actors with the highest positive utility also have the highest positive MTI, and the same is true for the negative values. This is unsurprising because of the similarities in the calculations between these two metrics. It is seen that the most positive MTI are those actors that act as primary producers and consumers of those producers at the lowest trophic level. The actors with the most negative cumulative MTI are the detritus and detritivore actors. Both of these are for the same reasons stated in the Utility Analysis section. While there is not new insight to be gained from that, there is from the cumulative absolute impact results. The actors with the largest cumulative absolute impact largely mimic the results of the largest negative impact. This means it consists mostly of detritus and detritivore actors. As stated, that means a change in biomass of these actors will result in the greatest change in biomass across the entire system.

As is the trend, there is not a clear actor type that dominates this analysis for the human-designed systems. However, similar to the ecosystems, there are similarities between these results and the Utility Analysis results. The actors with the highest positive MTI are similar to the actors with the highest positive utility, and the same is true for the actors with negative values. Also similar to the ecosystem results, the actors with the highest cumulative absolute impact are similar to those that have the highest negative impact. This shows that the actors that take in a lot of resources have a greater impact on the total system compared to all other actors. As with the other metrics shown here, it is beneficial to look more closely at an individual network to understand specific interactions. Table 15 shows the MTI results for two actors in the Central Arizona Phoenix Nitrogen network. These two actors, Humans and Near-surface atmosphere have the highest cumulative positive and negative impacts, respectively. For Humans, the two actors that are most positively impacts are the Wastewater and Landfills and Palo Verde actors. This is expected because an increase in the human population will lead to an increase in waste generated and thus more nitrogen being sent from the Humans actors to these two. The actor most negatively impacted by Humans are Humans themselves. This is explained by

Ulanowicz and Puccia in that the greatest threat to an organism is their own growth. As they increase and consume more, there will be less available to consume, thus causing internal competition leading to an overall negative impact (Ulanowicz and Puccia 1990).

Table 15 Mixed Trophic Impact results for Central Arizona Phoenix Nitrogen network showing how increase in two actors would lead to change in all other actors

	Humans	Near-surface atmosphere
Desert	-0.021	-0.389
Near-surface atmosphere	0.059	0.112
Crops	-0.036	-0.323
Dairies	-0.076	-0.275
Humans	-0.358	0.393
Pets	0.056	0.172
Wastewater	0.382	-0.561
Urban landscapes	-0.056	-0.172
Subsurface	0.028	0.016
Landfills and Palo Verde	0.164	0.006

Examining the Near-surface atmosphere impact interactions it can be seen there are the same number of positive and negative interactions compared with Humans, but the negative interactions have much greater values. Specifically, the Wastewater, Desert, Crops, and Dairies actors are all largely negatively impacted by an increase in the amount of nitrogen in the atmosphere actor. In this network, the atmosphere acts as a large sink for excess nitrogen, and as such it consumes more from these actors than it provides to them. Therefore, nitrogen content in other actors would decrease as the concentration of nitrogen increases in the atmosphere. The atmosphere inn this network acts similarly to the detrital actor of natural systems in that it collects the discarded flow from the other actors. It only consumes what is expelled to it as a result of bacterial transformation of nitrates/nitrites into elemental nitrogen (i.e. denitrification). An increase in this actor thus represents an increase in the transformation rate of nitrogen by the bacteria. These nuances exist within the human-designed systems, and it is important to inspect the results closely to understand those nuances. Even with this limitation, it can still prove to be useful in understanding the change in one actor given the change in another.

5.2.4 Control/Dependence Analysis

Similar to the other analysis in this chapter, the results are computed using the indirect matrices and are aggregated to identify those actors that exhibit the most Control or Dependence throughout the entire system. This aggregation is done by summing the total contribution each individual actor has to all other actors in regards to both metrics. Actors can have a zero summation for Control and Dependence. Zero cumulative Control occurs for actors in which the only inputs into these compartments is from outside of the system. Zero cumulative Dependence occurs for actors in which the only out flows from these compartments leaves the system. The Appendix in Table 61 and Table 62 show the top three actors in each system ranked by total Control and total Dependence. For the ecosystems, the actors top ranked in Control are many of the detrital actors. This includes many forms of sedimentary and particulate carbon. The actors top ranked in Dependence are lower in trophic levels including many primary producers such as phytoplankton. Again, for the UIEs, there is no clear actor type that dominates either the Control or

Dependence. Among all the networks, the actors that have a large ratio of inflow to outflow tend to have the highest Control. Conversely, the actors that have the opposite ratio tend to have the highest Dependence.

Figure 10 shows the Control/Dependence analysis results for the Central Arizona Phoenix nitrogen network. As shown, the second compartment, near-surface atmosphere, has the greatest cumulative Control in this system. It exhibits more control than any other actor on the majority of the other actors. It has a cumulative Control of 4.21 while the next highest value is the crops actor (compartment 3) with a value of 1.61. The “pets” actor (compartment 6) has no control over any other actors in the system. The Dependence results are more distributed for this network. The “pets” actor has the largest Dependence value of 2.41, with the next highest value being the humans actor (compartment 5) with a value of 1.48. The landfills and Palo Verde actor (compartment 10) has zero value for cumulative Dependence. Figure 11 shows the heatmap results for the St. Marks Seagrass ecosystem. There are a number of actors that have no Control or Dependence due to the size of the network. The actor with the most Control is the last row which is sediment particulate organic carbon, a detritus actor. The actor with the most Dependence is the benthic bacteria actor.

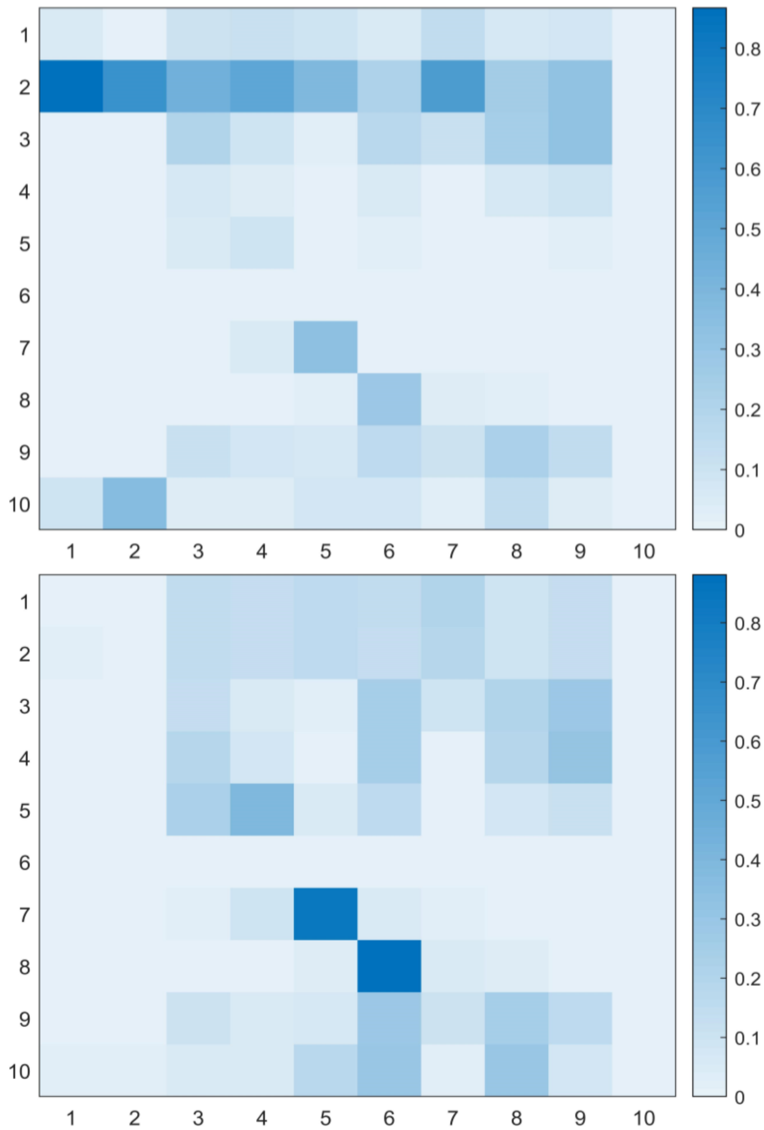


Figure 10 Control (top) and Dependence (bottom) results for the Central Arizona Phoenix Nitrogen network. For Control, each column sums to one, with each row representing the contribution to control of that specific compartment. The opposite is true for Dependence with each row summing to one and each column representing the contribution to Dependence for that actor. Total contribution of each actor for Control is calculated by summing the rows, while the total contribution for Dependence is calculated by summing the columns of the respective matrices.

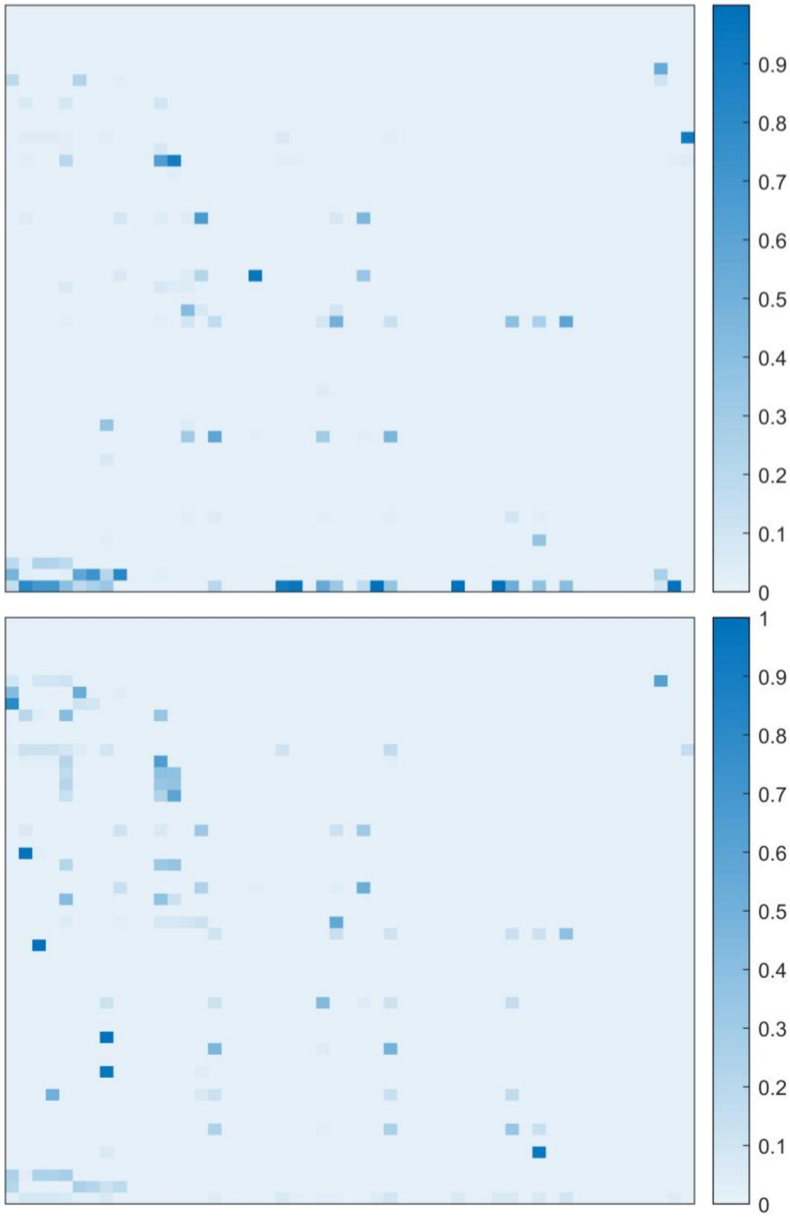


Figure 11 Control (top) and Dependence (bottom) results for the St. Marks Seagrass ecosystem

5.2.5 *Combined Analysis*

As stated, Centrality only accounts for the structure of a system, while MTI accounts for both the structure and flow. Therefore, it is important to analyze these together to see if there are any major differences or similarities between the two. While their calculations differ, they both analyze the importance of each actor relative to the other actors.

As shown in Table 16, for 26 of the 31 ecosystems, the same actor is both the top ranked actor based on the averaged centrality rank and has the largest cumulative absolute impact from the MTI assessment. These actors mainly consist of detritus and particulate organic carbon (a form of detritus). For the MTI assessment, all top actors are detritus and for the Centrality assessment, all but 3 of the top actors are detritus. Those other 3 are insects which act as detritivores in these systems, feeding off detritus.

Table 16 Highest ranked actors based on MTI and Centrality analysis for Food Webs

Ecosystem	Most Impactful	Most Central
Mangroves (dry)	Particulate Organic Carbon	Carbon in Sediment
Mangroves (wet)	Particulate Organic Carbon	Carbon in Sediment
Middle Atlantic Bight	Detritus- Particulate Organic Carbon	Detritus- Particulate Organic Carbon
Southern New England Bight	Detritus- Particulate Organic Carbon	Detritus- Particulate Organic Carbon
Georges Bank	Detritus- Particulate Organic Carbon	Detritus- Particulate Organic Carbon
Gulf of Maine	Detritus- Particulate Organic Carbon	Detritus- Particulate Organic Carbon
Graminoids (dry)	Refractory Detritus	Refractory Detritus
Graminoids (wet)	Refractory Detritus	Refractory Detritus
Florida Bay (dry)	Water Particulate Organic Carbon	Water Particulate Organic Carbon
Florida Bay (wet)	Water Particulate Organic Carbon	Water Particulate Organic Carbon
Lake Oneida (pre-ZM)	Sedimented Detritus	Insects
Lake Oneida (post-ZM)	Sedimented Detritus	Insects

Bay of Quinte (pre-ZM)	Sedimented Detritus	Sedimented Detritus
Bay of Quinte (post-ZM)	Sedimented Detritus	Insects
Cypress (wet)	Vertebrate Detritus	Vertebrate Detritus
Cypress (dry)	Vertebrate Detritus	Vertebrate Detritus
Sylt-Romo Bight	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
Narragansett Bay	Detritus	Detritus
Neuse Estuary (late summer 1998)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
Neuse Estuary (early summer 1998)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
Neuse Estuary (early summer 1997)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
St. Marks Seagrass, site 1 (Feb.)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
St. Marks Seagrass, site 2 (Jan.)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
Northern Benguela Upwelling	Particulate Organic Carbon	Particulate Organic Carbon
St. Marks Seagrass, site 4 (Feb.)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
St. Marks Seagrass, site 1 (Jan.)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
St. Marks Seagrass, site 2 (Feb.)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
Neuse Estuary (late summer 1998)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
St. Marks Seagrass, site 3 (Jan.)	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon
Bothnian Sea	Sedimentary Carbon	Sedimentary Carbon
Bothnian Bay	Sedimentary Carbon	Sedimentary Carbon

The human-designed systems were analyzed in the same way and their results are shown in Table 17 and Table 18. The UIEs were analyzed using both Centrality and MTI, but the EIPs were analyzed only with Centrality because these networks only include structural connections and do not include flow information. For the UIEs, 18 of the 29 networks had the same actor with the highest impact and highest Centrality (including when two actors were tied for the highest value). These actors include industrial actors, the natural environment, and human actors. For the EIPs, there is a similar spread of actor types, with a larger amount being industrial actors. Also shown is whether the central actors acts as a recycler or not. A recycler in this context is an actor that takes in waste or discarded material and processes it in such a way that is made useful to another actor in the system. This is specifically in regards to the system and does not account for actors that produce useful material that is exported from the system. Of the most central actors in the UIEs, only 2 of the 29 were recycling actors, and 17 of the 48 most central actors were recycling actors in the EIPs.

Table 17 Highest ranked actors based on MTI and Centrality analysis for UIEs. (*) indicates that the actor functions as a recycler in the network

UIE	Most Impactful	Most Central
Central Arizona Phoenix Nitrogen	Near-Surface Atmosphere	Crops
Central Arizona Phoenix Nitrogen, no Landfill	Near-Surface Atmosphere	Crops
Toronto Nitrogen 1990	Human Bodies	Human Bodies
Toronto Nitrogen 2001	Human Bodies	Human Bodies
Toronto Nitrogen 2004	Human Bodies	Human Bodies
Swiss Lowlands Timber	Incineration and waste management	Incineration and waste management
Swiss Lowlands Timber 87% Recycling	Incineration and waste management	Incineration and waste management
Swiss Lowlands Timber 100% Recycling	Production and trade of timber products	Production and trade of paper products*
Central Arizona Phoenix Wastewater Nitrogen	Wastewater treatment plants	Wastewater treatment plants*
Trinket Island Energy	Human Nutrition	Human Nutrition
Xiamen Energy	Industry	Electric
Beijing Energy 1995	Energy Transformation Sector	Energy Consumption sector
Beijing Energy 2000	Energy Consumption Sector	Energy Consumption sector
Beijing Energy 2005	Energy Consumption Sector	Energy Consumption sector
Beijing Energy 2007	Energy Consumption Sector	Energy Transformation sector
Beijing Emergy	Industrial Sector	Equally ranked
Tianjin Emergy	Industrial Sector	Equally ranked
Shanghai Emergy	Industrial Sector	Equally ranked
Chongqing Emergy	Agricultural Sector	Equally ranked
Suzhou Material	Agriculture	Other Manufacturing
Vienna Carbon	Domestic Sector	Domestic Sector
Stockholm Nitrogen	Air	Air
Stockholm Phosphorus	Service	Service
Beijing Nitrogen 1996	Atmosphere	Atmosphere
Beijing Nitrogen 2000	Atmosphere	Atmosphere
Beijing Nitrogen 2004	Atmosphere	Atmosphere
Beijing Nitrogen 2008	Atmosphere	Atmosphere
Beijing Nitrogen 2012	Atmosphere	Atmosphere
Gavle Phosphorus	Population Centre	Population Centre

Table 18 Highest ranked actors based on Centrality analysis for EIPs. (*) indicates that the actor functions as a recycler in the network

EIP	Most Central
Green Triangle	Composting and Nursery / Garden Center*
Pomacle-Bazancourt	Champtor
Renova	Agriculture / Aquaculture
Clark Special Economic Zone	Power Plant and Grey Water Processing*
Copper Industry Web	Scrap Dealers (large)*
Kytakyushu	Resource Recovery facility*
Kwinana	Chemical and fertilizer production
Ulsan Industrial Park	Y Wastewater Treatment Facility*
Humber ISP	Refineries
Uimaharju Forest Industry Park	Pulp Mill
UPM Kymi pulp and paper mill	Pulp Mill
Harjavalta Industrial Area	Porin Iampovoima Oy
GERIPA	Biodigestor*
Kawasaki	Commercial/Industrial/Municipal waste collectors*
Kymi	Pulp and Paper Plant*
Burnside	Manufacturing
Devens	Southern Container
Suzhou	Thin-film transistor liquid crystal display manufacturing
Guitang Sugarcane EIP Project	Sugar Refinery
Tianjin	Landscaping company
Guayama	AES Cogeneration Plant*
Scotia Investments	Scotia Recycling Inc.*
Kalundborg	ASNAES Power Station
Seshasayee Paper and Board Ltd	Sugar Production
Mongstad	CHP Plant
An Son Village	Biodigestor and Pig Farming*
AES Thames	Craft Brewery
Brownsville	Ballasts
Barceloneta	Pharmaceutical Firms
Red Hills EcoPlex	Power Generation
Fushan Farms	Biogas Generator 1*
Nanning Sugar Company	Sugar Production
Monfort Boys Town	Anaerobic Bio-digester*
Tunweni Brewery	Pig farming
Lower Mississippi Corridor	Ammonia Plant

Stoneyfield Londonderry	Wastewater treatment*
PV Symbiosis Prop	Muni. Recycle
Wallingford	Polymer Fabrication
Styrian Recycling Network	Iron Manufacturing Industry and Cement Plant 2
Landskrona	District heater
Jyvaskyla	Rauhalahti Power Plant*
NIA-KIADB	Oil Extraction Facility*
Lubei Industrial Park	Bromine plant
Gladstone 2008	Cement Australia
Pingdingshan Coal Mining Group	Building Materials Plant*
Triangle J	Compost Producer
Gladstone 2005	Cement and lime production
Connecticut Newsprint	Printing

5.3 Discussion

It is clear from the MTI and Centrality results the importance of detritus actors in natural ecosystems. In both the structural and flow analysis, these actors were consistently shown to be one of if not the most highly influential nodes in the network. This confirms previous research stating the importance of detritus and detritivore actors as they perform a critical function in ecosystems of processing discarded energy and nutrients. Detritus acts as a large sink for all of the waste generated in the system, so it would follow that these actors would fall "central" to these networks. This lack of detritus actors highlights one of the largest differences between natural and human-designed systems in that there is no consistent human equivalent to detritus and detritivore actors.

The issue of no detrital actors is in finding a similar equivalent to detritus and detritivores in the urban and industrial systems. Depending on the flow being measured, the ultimate fate of that flow will differ. For physical materials, Landfills act as the sink of the majority of physical materials (metal, plastic, etc.), which are deposited into landfills as "waste"; that is materials that in their present form are no longer useful to other actors. In this way, landfills act similar to detritus. However, there is a crucial difference in that this material is not broken down in landfills to be made useful again to the system. For energy systems, the "waste" is most often dissipated heat. This heat is sent to the ambient environment and is not able to be recovered once released. Waste heat recovery is possible and present within some of these systems, but the amount is much lower than that of the amount sent through detritus. The majority of these systems have some sort of recycling present, but as shown the most central actor is more often than not a recycler as defined. This is a vast difference from the Food Webs where all of the central actors act as recyclers. This highlights the need to not only increase recycling in these systems, but to make recycling central to these networks as opposed to a small offshoot of the main network.

The Utility Analysis continues to highlight the differences between natural systems and human-designed ones. Specifically looking at the percentage of mutualism relationships, it is clear that the UIEs on average have less of these interactions than the Food Webs. Additionally, there are more exploitative relationships. However, this does not take into account the compensatory flows mentioned in Section 3.2. The flows here only show one actor consuming another, but do not include the (likely) monetary flow that occurs in the reverse as a result. That mutual exchange would make most if not all of the relationships in the human-designed systems mutualistic as both parties are gaining something from the exchange. Because this does not exist in the natural world, this metrics does not capture those reverse flows, but this is an area of potential future work to better translate these relationship types to human-designed systems. Due to that lack, it is shown that there are more one-way harmful relationships and less two-way beneficial relationships in the human-designed systems.

However, looking at the mutualism index, we see that overall the UIEs have more positive links than negative with an average mutualism index above 1 while the Food Webs have the opposite with a mutualism index below 1. Other researchers have indicated that a higher value for this index indicates a better or more mature system (Tan et al. 2018), and that the goal should always be to increase this measure above 1 (Zhang, Yang, Fath, et al. 2010). This study shows many natural systems with a net negative utility. This could be explained by the structure of trophic levels. The higher trophic levels have fewer organisms than the lower trophic levels. This leads to more negative links overall as a greater number of things are being consumed than are consuming (more prey then predators). As a point of clarity, the mutualism index differs from the Utility relationships shown here. The relationships are defined by the pair of links between two actors, while the mutualism index takes into account only the one-way links throughout the network. Mutualism relationships only occur when both actors exhibit positive utility towards one another (+,+), but the mutualism index is increased with any positive link, regardless of the reciprocal interaction (i.e. +,- and +,0). For this reason, a network can have more mutualistic relationships than another, but have a lower mutualism index due to having fewer positive links overall. As a final comparison, the average percentages among four different Chinese urban energy metabolic systems was 54.1% exploit, 36.7% competition, and 9.2% mutualism (Zhang, Yang, Fath, et al. 2010). While these networks do not contain any neutral interactions, the percentages for exploit and mutualism are similar to those of the UIEs.

The Utility Analysis and MTI analysis provide similar results as expected given their similarity in calculation. The most positive actors based on total sum are those actors that have the highest ratio of consumed to consumption. The most negative actors are those that have the opposite with the highest ratio of consumption to consumed. This leads to the primary produces on these networks often times being the most positive, while the detritus type actors are often the most negative. These two trophic levels are critical to ecosystem functionality as they are the lowest level from which all resources originate. This type of structure is found in all of the ecosystems here. The UIEs do not show a clear trend in this same way. Some networks do not have a clear top actor in these categories. This is partially explained by the small size of these networks especially those with 3 or 4 actors. In those networks, all of the actors function in a similar way, and there are not enough interactions to distinguish between the critical actors and trophic levels.

Comparing the different analyses further, it is seen that Control and Dependence mimic the results of the Utility and MTI analysis. The actors that exhibit the most Control in these systems often are those that have the most negative Utility and MTI. These are the actors that take in a lot of flow from other actors, so it would make sense for them to be highly ranked in all of these categories. Meanwhile, the actors that have the must Dependence are often the actors with the most positive utility and MTI. These actors give the most to the system, meaning there is a high dependence on them. As seen in Figure 10 and Figure 11, the majority of interactions result in no Control and Dependence. It appears that most actors are controlled by or dependent on a small number of other actors. Since this analysis takes all path lengths into consideration, it shows how flow is funneled down to the waste collectors which exhibit a high amount of control and how the inflow from the lower trophic levels are distributed around the system resulting in high dependence on them.

Given the similarities in the actors identified by these results, it may be assumed that all of these metrics are unnecessary as they provide the same information. This appears to be the case if one is only interested in the high level ranking of actors to understand which are critical to the system. However, looking at the pair-wise interactions between actors shows the differences between the analysis more clearly. This allows researchers to identify where there are mutually beneficial relationships, how actors will change in reaction to a system change, and which actors have a control over or dependence on another actor.

5.4 Conclusions

Through the many different types of analysis, it has been shown consistently the importance that primary producers and detrital actors contribute to ecological systems. In all categories, these actors seem to be the key fabric that allow these systems to function in the way that they do. This does not minimize the role that the other organisms play in these systems, because without those other actors, there would be no links present. Rather, it highlights these actors as the fundamental base from which these ecosystems can develop. They are critical in bringing in resources to the system and also at keeping those resources within the boundaries to ensure these systems are sustained. That same base does not exist within the human-designed systems. There is no uniformity across these systems as to what will provide resources and what will take in waste. These systems are obviously much more varied in the type of flows, so it is not the specific actor that is of interest, but rather if there is a similar functional role that is consistent amongst the networks. The identification and creation of these baseline, functional roles is critical to altering the human-designed systems to function more like their natural counterparts. In their current state, these systems can still benefit from this type of analysis by identifying those actors that do function in particular ways. These analyses showed where the major sources and sinks were in the human-designed systems, which provides focal points for how to enact the most change in these systems.

CHAPTER 6. DESIGN GUIDELINES FOR UIES

In the previous chapters, multiple natural and human-designed systems have been analyzed using ENA. In this chapter, all of that analysis is combined into a wholistic look at these systems. This chapter looks at how all of these metrics compare to one another and what is at the core of a high level of ecological performance. This includes using correlations for the single value metrics as well as qualitatively comparing systems to understand the differences and similarities between them. This analysis culminates in the creation of three design guidelines for urban-industrial systems that are meant to 1) increase ecological performance as measured by the ENA metrics and 2) increase the sustainability and resilience of these systems. Resilience in this context is defined by two of the four attributes: robustness and redundancy. This robustness is not the ecological Robustness, but rather the ability of the system to withstand stress or excess demand. This is done by creating systems that are adaptable to perturbation. In addition, these guidelines aim to increase redundancy of these systems to spread resources among multiple sources more similar to natural ecosystems.

Guidelines are chosen instead of principles or heuristics as they fall in between these two in terms of specificity, needed supporting evidence, and formalization. In this context, a guideline is defined as "a context-dependent directive, based on extensive experience and/or empirical evidence, which provides design process direction to increase the chance of reaching a successful solution" (Fu, Yang, and Wood 2016). The guidelines are informed by the analysis performed but are not wholly prescriptive in that they will produce the same results every time. However, these guidelines will be tested in the following chapter to test their validity and understand what (if any) changes should be made.

6.1 Correlations

The goal of the correlation analysis is to assess the degree to which ENA metrics predict one another. If so, these metrics can be seen as the key metrics for design guidelines given their ability to predict other metrics. A metric with strong correlations to other metrics could be the basis of a design guideline if that metric can be maximized. Examining potential correlations also could simplify ways to determine well performing network by homing in on a few metrics.

6.1.1 Correlation Analysis

A correlation analysis was conducted among the ENA metrics to better understand their relation to one another. This correlation was done by calculating the linear R-squared value between pairs of metrics used in the prior analysis. As shown in Chapter 3, many of the metrics are calculated with logarithms, meaning the linear correlations may not be the best way to compare metrics. However, this is a good way to compare across metrics that are calculated in different ways. Additionally, many of those logarithmic metrics have their own comparisons, such as the Robustness curve shown previously. These linear correlations allow for the comparison across the structure and flow-based metrics and can inform which metrics may best predict overall ecological performance.

Correlations were calculated between all pairwise combinations of 19 different measures for the 29 Food Webs and 31 UIEs and 10 structural measures for the 48 EIPs. The strength of the correlations was broken into four categories: strong correlation (R-squared between 1.00 and 0.75), moderately strong correlation (R-squared between 0.75 and 0.50), moderately weak correlation (R-squared between 0.50 and 0.25), and weak correlation (R-squared between 0.25 and 0.00). The number of correlations sorted by category are shown in Table 19, Table 20, and Table 21 for the Food Webs, UIEs, and EIPs, respectively. These tables have a multi-level sort on them, sorting by the greatest number of strong correlations first and progressively sorting by the weaker correlations.

For the Food Webs, Linkage Density and Vulnerability each have the strongest correlations with 5 other variables. Linkage Density, Generalization, and Vulnerability all are either strongly or moderately strongly correlated with other variables. The Specialized Predator Fraction has the fewest number of weak correlations. Sorted this way, the top 9 most correlated metrics are all structure-based metrics, while all but 2 of the bottom 10 are flow based metrics. Mutualism Index, Robustness, and Predator Prey Ratio have no strong or moderately strong correlations. Specifically, Prey Predator Ratio only has weak correlations.

Table 19 Correlations sorted by strength for 19 ENA metrics for 31 Food Webs

	1.00-0.75	**0.75-0.50**	**0.50-0.25**	**0.25-0.00**
Linkage Density	5	3	2	8
Vulnerability	5	3	2	8
Generalization	4	4	2	8
Links	4	1	4	9
Cyclicity	3	4	3	8
Specialized Predator Fraction	3	3	5	7
Single Source Percentage	2	5	3	8
Percentage of Connecting Actors	1	6	2	9
Actors	1	4	3	10
Finn Cycling Index	1	0	1	16
Mean Path Length	1	0	0	17
Alpha	0	2	6	10
Connectance	0	2	4	12
Average Mutual Information	0	1	7	10
Normalized StDev of AMI	0	1	3	14
Shannon Index	0	1	1	16
Mutualism Index	0	0	3	15
Robustness	0	0	1	17
Prey Predator Ratio	0	0	0	18

For the UIEs, Links and Linkage Density have the most strong correlations with 4 each. Links also has the most strong or moderately strong correlations with 5 total. Cyclicity and Actors have the fewest number of weak correlations, but Actors has no strong correlations, while Cyclicity has 3. Percentage Connecting Actors, Prey Predator Ratio, Mean Path Length, Mutualism Index, and Robustness do not have any strong or moderately strong correlations. Similar to the Food Webs, the top 9 metrics are all structure based, and 8 of the bottom 10 are flow based.

Table 20 Correlations sorted by strength for 19 ENA metrics for 29 UIEs

	1.00-0.75	0.75-0.50	0.50-0.25	0.25-0.00
Links	4	1	1	12
Linkage Density	4	0	2	12
Cyclicity	3	1	3	11
Vulnerability	3	1	0	14
Generalization	2	2	1	13
Single Source Percentage	1	1	2	14
Specialized Predator Fraction	1	1	2	14
Connectance	0	3	3	12
Actors	0	2	5	11
Average Mutual Information	0	2	3	13
Shannon Index	0	2	3	13
Normalized StDev of AMI	0	2	3	13
Finn Cycling Index	0	1	2	15
Alpha	0	1	0	17
Percentage of Connecting Actors	0	0	6	12
Prey Predator Ratio	0	0	1	17
Mean Path Length	0	0	1	17
Mutualism Index	0	0	0	18
Robustness	0	0	0	18

There are no strong correlations for the EIP dataset. Linkage Density has the most moderately strong correlations with 3, with Generalization having 2 strong correlations, and 5 other metrics having a single strong correlation. Connectance and Prey Predator Ratio only have moderately weak and weak correlations and Percentage of Connecting Actors only has weak correlations.

Table 21 Correlations sorted by strength for 10 ENA metrics for 48 EIPs

	1.00-0.75	0.75-0.50	0.50-0.25	0.25-0.00
Linkage Density	0	3	3	3
Generalization	0	2	3	4
Vulnerability	0	1	3	5
Links	0	1	3	5
Cyclicity	0	1	2	6
Specialized Predator Fraction	0	1	2	6
Actors	0	1	1	7
Connectance	0	0	2	7
Prey Predator Ratio	0	0	1	8
Percentage of Connecting Actors	0	0	0	9

Across the three datasets, Linkage Density has the strongest correlations to the other ENA metrics and is worth further investigation. Figure 12 shows all of the correlations for Linkage Density across the Food Webs, UIEs, and EIPs. Many of these strong correlations are with Generalization, Vulnerability, and Links. These are all related as they are concerned with the number of links and all increase as that the network becomes more connected. More interestingly, Linkage Density has either a strong or moderately strong correlation with Cyclicity in the datasets. This indicates that there is a correlation between how well connected a system is and how many cycles are present within that system. More links will not always lead to more cycles, but across these systems, it shows how these two are more often than not correlated. Most all of the correlations between Linkage Density and the flow-based metrics are weak or moderately weak. This means that the level of connection is not a good indicator of the flow-based metrics. Additionally, Table 22 shows whether the correlations between Linkage Density and the other metrics are positive or negative. For the structure metrics, 23 of the 27 correlations across the three datasets are positive. For the flow metrics, 13 of the 18 correlations across the two flow datasets are negative.

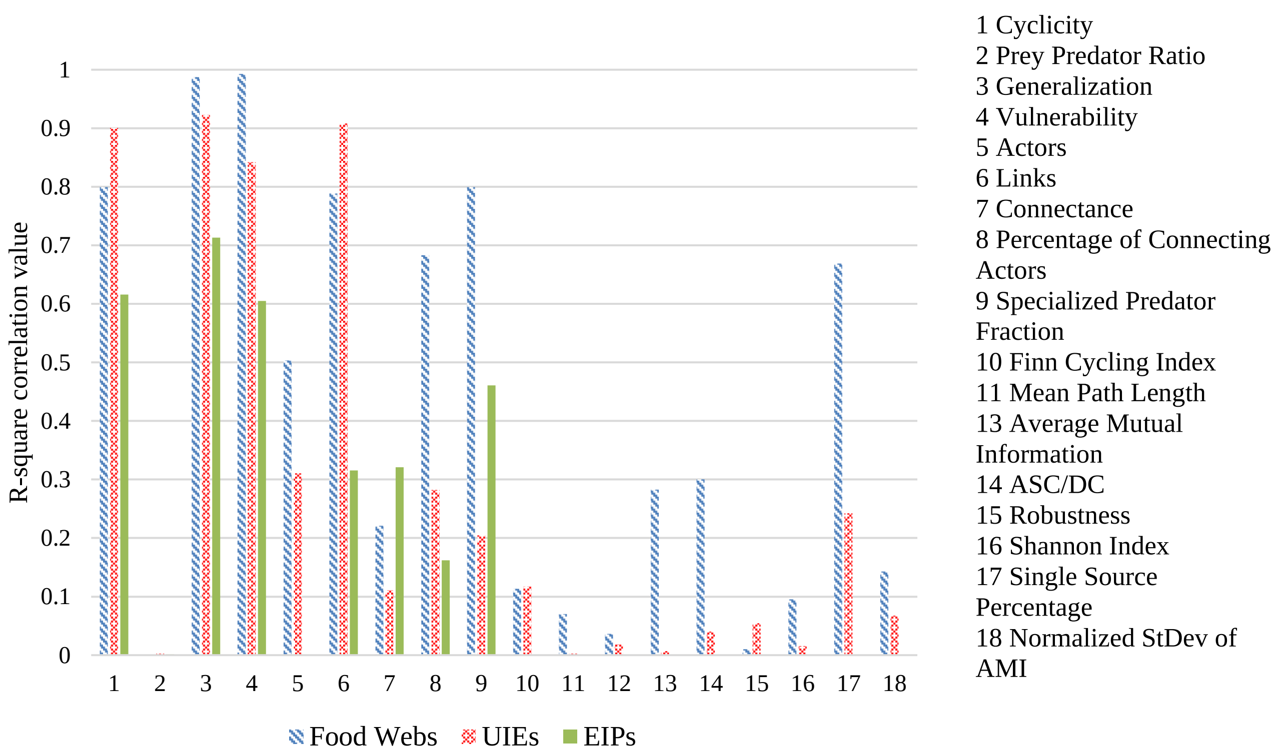


Figure 12 R-square correlation values between Linkage Density and other ENA metrics

Table 23 shows the number of positive and negative correlations for each dataset. As seen, the majority of the structure to structure correlations are positive ones for each dataset and when all three are combined. Most of the structure to flow correlations are negative for both Food Webs and UIEs. The flow to flow correlations are mostly positive for the Food Webs with 42 of the 72 correlations being positive. However, these are mostly negative for the UIEs with 44 of the 72 correlations being negative.

Table 22 Signs of correlations between Linkage Density and other ENA metrics

	Food Webs	UIEs	EIPs
Cyclicity	+	+	+
Prey Predator Ratio	+	+	+
Generalization	+	+	+
Vulnerability	+	+	+
Actors	+	+	-
Links	+	+	+
Connectance	+	+	+
Percentage of Connecting Actors	+	+	+
Specialized Predator Fraction	-	-	-
Mutualism Index	-	-	
Finn Cycling Index	-	+	
Mean Path Length	-	+	
Average Mutual Information	-	-	
ASC/DC	-	-	
Robustness	-	+	
Shannon Index	+	+	
Single Prey Predators + Imports	-	-	

Normalized StDev of AMI	-	-

Table 23 Number of positive and negative correlations for all ENA metrics shown for structure to structure (S-S) metrics, structure to flow (S-F) metrics, and flow to flow (F-F) metrics

	S-S	**S-F**	**F-F**
Food Webs			
Positive	64	29	42
Negative	26	61	30
Total	90	90	72
UIEs			
Positive	66	38	28
Negative	24	52	44
Total	90	90	72
EIPs			
Positive	54		
Negative	36		
Total	90		
Combined			
Positive	184	67	70
Negative	86	113	74
Total	270	180	144

6.1.2 Conclusions of Correlation Analysis

Correlations analysis of ENA metrics indicates that they are not strongly associated with one another in general. There are some particular instances of strong correlations within each of the datasets, but the pattern is not consistent across all three datasets. The strongest correlations are between some of the structural metrics, but these correlations are weaker within the purely structural dataset (EIPs) than in the two flow-based ones (Food Webs and UIEs). There are mostly weak correlations between the structural and flow metrics, and this is also true between the flow metrics. Metrics calculated in Food Webs are most strongly correlated to one another when compared to those from the other two datasets, but the majority of these correlations are weak. This may suggest different food webs are structured or constrained by the same forces, as they are more similar to one another than the human-designed systems are to one another. Further, there is little pattern regarding the sign of the association. The structure to structure correlations mostly are positive, while the structure to flow are mostly negative, and the flow to flow are about half positive and half negative.

No single metric or subset of metrics predicts the other metrics. Additionally, it is hard to predict the effect (positive or negative) changing one metric would have on another. The lack of correlations shows the uniqueness of each metric in describing a specific network characteristic. Therefore, it is important to analyze all metrics to fully understand a system. There are not specific metrics to focus on that will increase network attributes in all areas (cycling, less waste, fewer exports, etc.). Instead, designers can choose which aspects they want to improve and can focus on the metrics for those aspects. These changes must be done on a case by case (and likely iterative) basis to accomplish the improvements desired. This means there is not a clear and concise design guideline than can be drawn from this analysis. The correlations are too varied to reduce this down to a single statement that will be true for all systems.

6.2 Qualitative Network Analysis

The quantitative analysis previously shown is very useful in ascribing values to these systems so that they can be compared. However, this type of analysis can only describe what is being measured and calculated, ignoring some of the many nuances of these complex systems. For that reason, it is useful to perform a more qualitative analysis on the UIEs that incorporate some of the ENA metrics to better understand why a particular system would outperform another. Through the observations of these systems, it should be possible to extrapolate design guidelines that are not so focused on the ENA metrics. While the metrics have been shown to be useful, the metrics are not able to describe the function an actor in one system has in comparison to that same actor in another system. The goal of this analysis is to provide that and other insights that are not immediately clear unless each system is examined closer. This starts by looking specifically at the nitrogen networks within the UIE dataset and then examines more broadly the remaining networks.

6.2.1 Nitrogen Networks

As mentioned in Chapter 4, there are many nutrient networks in the UIE dataset, and specifically 12 nitrogen networks. Given this number, it is interesting to examine these networks with more depth to understand the differences between them and how these translate to differences in ecological performance. This examination includes both the quantitative ENA metrics previously presented as well as qualitative observations about the networks individually and in relation to one another. While there are 12 networks, these come from 5 different sources, some of which include multiple networks. These multiple networks include the same network analyzed in multiple years. For this analysis, these multi-year networks are grouped and discussed as if they were a single network. The differences between years is not significant enough to warrant an individual analysis of each as the main areas of interest of the types of actors in each network and the connections between them.

6.2.1.1 Central Arizona-Phoenix

This network has 10 actors, the majority of which (80%) act as importers to the system. Additionally, it contains one main SCC that encompasses 8 of the 10 actors. This SCC achieves fair bit of cycling, with this network having a higher value for Cyclicity and FCI than many of the other nitrogen networks. The Near-Surface Atmosphere and Crops actors have the highest system activity with many nodes connect both to and from these actors with relatively large flow amounts. Also, these actors contribute a lot to the cycling of this network as they are found on many of the cyclic pathways and takes in the “waste” from other actors. The Human actor, however, does not contribute to the cycling at all as it does not take in any waste and only acts as a consumer and waste generator. Of the nitrogen networks, this one has the lowest value for ASC/DC, meaning it has the most built in redundancy.

6.2.1.2 Toronto

This network has 6 actors that is centered around the Human Bodies actor and focused on the nitrogen in food and waste. The single input is Available Food which drives the flow through the entire system. This comes into the Human Bodies, which is then exported through various pathways. The amount of nitrogen that cycles in this system is extremely small with only a single loop and a very low value for FCI. The system boundary is drawn tight, not showing some of the interactions and feedback loops such as the relationship between the atmosphere and the land through nitrogen fixation. Additionally, although this is food centric, it does not include an agricultural actor.

6.2.1.3 Central Arizona-Phoenix Wastewater

This network has 6 actors and is focused on wastewater. There is a single input of wastewater which flows into the Wastewater Treatment Plants and is distributed to all other actors from there. There is no cycling in this network of any kind as shown by the zero values for Cyclicity and FCI. This network functions similar to the Toronto network in that there is one central actor that takes in the sole input and is then dispersed to many other actors for export from the system. Very few pathways that are longer than two actors. Unlike other nitrogen networks, this one does not include an explicit human actor. The ultimate fate of most of this nitrogen is the atmosphere, but this is not drawn within the system boundary and instead acts as an export. This is much more limited than the more general Central Arizona-Phoenix network because it only focuses on the wastewater and does not include many of the other pathways for the nitrogen.

6.2.1.4 Beijing

This is the largest of the nitrogen networks at 16 actors. It does not have a specific focus on a particular aspect of the nitrogen cycle, but instead encompasses all of the nitrogen interactions within the area. It is most similar to the Central Arizona-Phoenix nitrogen network in terms of the scope of the boundary and types of actors that are included. Similar to that network, the atmosphere plays a critical role with it being the most central actor in this network and being a key part of many of the cyclic pathways. It has more specialized actors (such as Aquaculture) when compared with the other networks. This network has the highest value for Cyclicity among the nitrogen networks, and the second highest among all of the UIEs. It has the second highest value for FCI among the nitrogen networks. All of the actors are a part of a SCC with one being a grouping of 10 and the other 6 being grouped within another.

6.2.1.5 Stockholm

This network is the second largest nitrogen network with 11 actors. This is a general network that does not have a specific nitrogen focus. Although it has similar actors to the Central Arizona-Phoenix and Beijing networks, it does not include all of the same links, thus having a lower linkage density than both of those networks. This network has the median value for Cyclicity for the nitrogen networks, with all of the cycling being contained within three of the actors (Air, Land, and Waste Management). However, the FCI is almost zero (0.001) meaning that even though cyclic pathways exist, the amount of nitrogen that is cycled is extremely small compared with the total amount of flow. The atmosphere actor is the most central actor as many actors send flow there. Waste management is the second most central because of the similar trend to take in flow from many different actors.

6.2.1.6 Observations of Nitrogen Networks

Amongst the nitrogen networks, the Beijing network performs the best while the Toronto network performs the worst. The difference between the better and worse performing networks appears to stem from both where the boundary is drawn the scope of the actors. The networks that draw a bigger boundary and include things like the natural environment, agriculture, and some of the industrial processes have more connections and better performance. Those networks that limit the scope to just the import of food and its fate (Toronto) or the processing of wastewater (Central Arizona-Phoenix wastewater) ignore many of the other connections that could be used and therefore have little to no cycling. The atmosphere is a key component to nitrogen networks which makes sense considering the amount of nitrogen in the atmosphere and the many nitrogen processes (fixation, deposition, etc.). In general, the bigger networks perform better, mainly due to the fact that they have more actors that include meaningful links. It is not as much about the size as the types of actors that are there because the bigger networks have a larger boundary and larger scope.

6.2.2 Other Networks

The other UIE networks are similar to the performance and structure of the nitrogen networks. The networks with larger scopes and boundaries have higher ecological performance than those that do not. Additionally, there are many of these networks that structurally show many cycling loops but have so little flow within those loops that the FCI is basically zero. There are similar linear pathways in these systems with the ultimate fate of the majority of resources being in a waste site or being dissipated. This dissipation is expected for the energy systems as all energy is eventually dissipated as heat, but the physical resources such as phosphorus or timber have a much greater capacity to be recycled within the system than they currently exhibit. Many of these systems contain nonspecific actors that do not give detail as to the exact interactions that are occurring between components. These nonspecific actors also encompass many interactions that are occurring in the UIE and are not being modeled.

6.3 Summary of UIE and Ecosystem Comparison

Before the design guidelines are outlined, it is useful to summarize the key differences that have been identified between the UIEs and natural ecosystems. These key differences are the fundamental basis for the design guidelines that follow as the goal of this research is to create human-designed systems that function more like their natural counterparts. The summary of these differences are as follows.

- Ecosystems are much larger with a higher degree of connectivity.
- There are longer pathways in ecosystems.
- There are a greater number of actors that act as connectors between two other actors in ecosystems.
- A greater number of actors function as importers in the UIEs than in the ecosystems.
- There is a larger percentage of actors that rely on a single prey or on outside resources in the human-designed systems than in the ecosystems.
- There is consistently a clear central actor in the ecosystems in the form of the detrital actor that processes the waste of the system. There is no clear central actor in the human-designed systems as well as a lack of the recycling functional group

Each of these is informed by the results presented in Chapters 4, 5, and 6. While this does not present all of the differences, these are fundamental to the performance gap that exists between these systems. Additionally, it is useful to clearly define the typical flow pathways that occur within these systems to further highlight the differences between them.

6.3.1 Ecosystem Energy and Material Flow

Imports occur mainly through the primary producers. These producers preform photosynthesis to generate useful energy for the rest of the ecosystem. In this way, the main import is solar energy. Energy and material move up the trophic levels with energy and heat being dissipated along the way. There is not much cycling that occurs within these interactions as this is a linear process. Any waste (dead organic matter) produced is collected in detritus. Detritus interacts with all trophic levels by receiving from almost all organisms. The detritus itself is not a living organism, but rather a source of all dead organic matter in the system. The detritus is processed by detritivores upcycling the waste to be useful again. The only exports from the system is waste that leaves the system boundary. This would likely be processed by detritivores in a different system so there is no waste build up anywhere. In this way, everything will be processed eventually.

6.3.2 Human-Designed Energy and Material Flow

The human-designed systems are much more varied and therefore harder to generalize the typical flow path. For the sake of consistency and comparison to the natural system flow, this will examine a combination of energy and resources to generate energy to most closely mimic the natural ecosystem. Imports in these systems are typically some form of natural fuel (coal, natural gas, etc.) that has been harvested outside the system boundary and brought into the system. This fuel is brought to a centralized actor that will burn it to generate electricity for the remaining actors in the system. Some of this fuel may be imported directly to those other actors, but this is not always the case. Once the fuel is used, it is discarded, often sent to a landfill and no longer useful to the system. The electricity flows to the actors to be used and is ultimately dissipated as heat. Similar to the natural systems, the energy used for electricity cannot be recovered once it is used. The biggest difference lies in the material. This fuel has a single useful life before it is discarded, while the nutrients in natural systems are cycled indefinitely.

6.4 Design Guidelines

As outlined in Chapter 3, there are many fundamental differences between human-designed systems and natural ecosystems. As a result, the human-designed systems cannot be designed to perfectly mimic the ecosystems, although they can be designed to recreate some of the positive attributes of natural systems. These design guidelines (DGs) are not intended to produce systems that mimic ecosystems exactly, but rather to promote the ability to recreate positive ecosystem functions in urban and industrial systems.

The major gaps in performance between human and natural shown in Section 4.3 relate to the lack of complexity and cycling and the greater amount of specialized predators in the human-designed systems. These design guidelines are proposed to address those specific gaps. What follows is a general design process and procedure to be used when modifying human-designed networks. From this process, three specific design guidelines are stated that are hypothesized to reduce the performance gaps previously shown. These guidelines outline specific questions and metrics that should be examined when designing these systems. Additional guidelines could be created to modify other aspects of these networks and increase other metrics accordingly, but this dissertation focuses on the characteristics mentioned.

6.4.1 Design Process

A general procedure was created to show the analysis and design process to create biologically-inspired human-designed systems. This process is used in the following chapter to modify and test various human-designed systems. This is a potentially iterative process if the exact goals are not met with the initial modifications. Also, these are general steps that may require multiple smaller steps in between to fully complete the process. This is not an exhaustive design process, but rather an overall guidance. The design and analysis procedure is:

1. Define the network appropriately and perform ENA. This provides the quantitative results from which to compare and understand how to change the system.

2. Examine results to identify aspects where the network is not performing as desired. The results will give guidance as to how the network can be improved based on specific goals.

3. Compare to similar networks. A qualitative and quantitative comparison (using the ENA metrics) can identify gaps (both structural and functional) in the network of interest. This can provide a starting point for modification.

4. Generate design modifications to address specific concerns. The modifications should have specific outcomes they hope to achieve. This primarily involves altering the flows between actors or adding new actors.

5. Implement modifications and test with ENA. Implementation of the modifications can be guided by similar networks to understand which specific actors to add or how flow magnitudes between actors should change. ENA can then be performed, and the results compared with the original network to quantify the impact of the modifications.

6.4.2 DG1: Include all baseline actors for a specific network type to properly model and show performance

Some of the difference in the ecological metrics between the UIEs lies in the inclusion or exclusion of critical actors. These actors may be present but not modeled as part of the system or they may be lacking. The inclusion of all of these baseline actors allows for the possibility of more interactions and synergies that can improve overall performance.

Other networks, particularly those of the same type provide a gauge of ecological performance and general structure. These can provide insight into the modifications that could be implemented in a poorly performing network. Quantitatively the ENA metrics can be used to compare, but it is equally important to ask more qualitative questions to understand the differences in networks. How does this network compare to networks of the same flow type? Does it include all of the same actors? Are these actors part of the system even though the connections and flows are not explicit? If so, how can the flows be defined and are these actors in connected in the same ways as in well performing systems? If not, how can those be added? These questions examine what is potentially missing from the network and how that can be added. This requires some knowledge and/or research about what is typical and/or potentially beneficial for a specific network type. In tandem with the ecological results, this comparison can guide the design of modifications to create the highest performing systems. When too focused on a single aspect of the flow (such as only the nitrogen found in wastewater), networks may fail to include the complexity that is inherent within well performing systems. This is shown in Section 4.3 by the increased performance of UIEs that included specific actor types. Also, in the qualitative analysis in Section 6.2 the better performing nitrogen networks included a greater number and variety of actors. A greater number of functional roles may make these systems look more like their natural counterparts as the natural ecosystems include a much greater number of actors and connections representing many different functions and trophic levels.

6.4.3 DG2: Implement waste recovery and recycling actors to increase cycling performance and resource utilization

It is important to start by understanding the flow represented in the network and common ways this flow is cycled. For example, water is easily cycled by treating wastewater and sending it back to the source from which it was drawn. Quantitatively, this means looking at the cycling metrics of Cyclicity and Finn Cycling Index. Are these values below average for the human-designed networks or more specifically the network type that is being examined? If so, cycling could be a focus of the modifications. Even if the values are average or above average, there is almost always greater potential for cycling if a new technology is added or the network is reconfigured. The impact of suggested modifications is then examined by calculating these same metrics in the new network configuration.

Strongly Connected Components should be considered as they highlight which actors are involved in cycling. One question should be, is it possible to include more actors in network cycling? Modifications to increase cycling are largely network dependent, but as mentioned, there are specific ways certain types of flow are commonly cycled. Some of the ways cycling can occur may be unique to the network at hand such as the presence of a landfill that captures excess methane gas to be used for energy elsewhere in the network.

As mentioned in Sections 5.2 and 5.3, all of the ecosystems are reliant on a central detritus actor to collect waste that can then be processed by detritivore. This function is basically non-existent in the urban-industrial systems and if it is present, it is proportionally much smaller than those of the ecosystems. By increasing the utilization of recyclers in these systems, the flows into and out of the boundary can be greatly reduced. More recycling will mean less waste is exported from the system because more of it remains in loops within the system. On the other side of the network, this will also reduce the amount of imports that are needed to sustain a system as less virgin material will be needed due to the increase in recycled material present. This also can aid the resilience (i.e. redundancy) of the system by adding another source of resources that expands beyond an outside importer. This issue is addressed more in the next guidelines. More recyclers mean pathways are increased showing a greater degree of resource utilization.

6.4.4 DG3: Introduce additional sources of resources to create more resilient systems

Too much reliance on single sources can create networks that are not resilient. This can be quantified by looking at the Specialized Predator Fraction and the Single Source Percentage. If a network has a high value for these metrics, this is a potentially very brittle system. As seen in Section 4.3, the human-engineered systems have much higher values for these metrics than the natural systems. This can be remedied by adding additional sources of resources to the network and is primarily done through altering the actors already present or bringing new actors into the network. As with cycling, the exact way this is done will be dependent on the network type and existing configuration. However, it is important to note the additional source should be within the system as opposed to outside the system. Outside sources are likely not geographically collocated and therefore are going to have a greater environmental impact to import those flows, while also better mimicking natural systems. This addresses concerns of resilience (i.e. robustness) as well as increases resource utilization.

6.4.5 Other Considerations

These aspects of the system analysis and design do not fall within the design guidelines outlined but are related and should be kept in mind.

Central actors – The central actors to a network are those that are highly connected and process a large of amount of flow as it passes through the system. This is quantified by Centrality and the other metrics shown in Chapter 5. When looking at these metrics, these are important questions to ask. Is there one central actor that is consistently ranked at the top of all metrics? If so, why is that? If the central actor fails or stops operating does the entire system fail? How could that be remedied? Examining the central actor will quantify the priorities of a system by highlighting where resources go. These actors have the largest influence on the network and therefore are ideal candidates to alter to affect greater network change.

Sources and sinks – Related to the central actors are those identified to be a source or sink within the system. These actors either provide a lot to the system (source) or take in a lot (sink) relative to the total flow. These can be identified with the flow metrics of Chapter 5 (Utility, Mixed Trophic Impact, Control, and Dependence). For these actors, these are questions to be examined. Why is something created to be a source or sink? Does this effect the redundancy of the system (either positive or negative)? Could these resources be more equitably shared? How do the sinks process the flow? These actors may need further examination to accomplish the goals set forth.

Imports and exports – The amount of imports into and exports out of a system determine aspects of the system resiliency. A system largely reliant on imports may not have the means to sustain if those external actors are changed in some way. Additionally, exports out of a system are potentially useful resources that could be utilized within the system elsewhere, reducing the amount of import needed. While there is not a specific ENA metric that examines these values, it can easily be quantified. Specifically, these questions can be asked. What imports could be met by actors within the system? What exports could be processed by actors within the system? What percentage of resources (e.g. food) are coming from outside the system? Could this be reduced? With the implementation of the design guidelines, the amount of external flow should change, and it is important to quantify that change to show the increased performance.

6.5 Conclusions and Summary

In this chapter, a correlation analysis was conducted between the ecological metrics showing an overall weak correlation. While the ecosystems had stronger correlations than the human-designed systems, there was still not enough of a correlation to identify key metrics that predict total ecological performance. Each metric is unique and therefore has value in the analysis of systems. Additionally, in this chapter, a qualitative analysis was conducted on the UIEs to better understand the performance gap that exists between them. This pointed to several key factors that includes the scope of the networks, where the boundaries were drawn, levels of aggregation, and what actors were included. These analyses combined with the previous chapters culminated in the creation of three design guidelines to improve the performance of urban-industrial systems. These guidelines center around modeling the systems to include all real-world connections, as well as increasing the utilization of recycling components. In the following chapter, these guidelines will be tested and validated using the UIEs previously analyzed as well as additional systems that have been generated.

CHAPTER 7. TESTING OF ECOLOGICALLY DERIVED DESIGN GUIDELINES IN URBAN-INDUSTRIAL ECOSYSTEMS

In this chapter, the design guidelines outlined in the previous chapter are tested using a number of case studies. These case studies include some of the UIEs gathered from literature, an automotive production network, a Chinese steel manufacturing network, and the network around the city of Fayetteville, AR. Each case study provides a different look at how the design principles can be implemented. For each network, there are different modification scenarios proposed that address one or more of the design principles. The baseline networks are compared to these modified networks using ENA and other analysis to understand the result of the modifications. The results show increased ecological performance as well as reduction in emissions and amount of flow imported into these systems, thus proving the effectiveness of the design principles.

7.1 Modification of UIEs

Select UIEs were modified to test the design guidelines. As stated previously, all of these networks are taken from academic sources with limited information regarding how they were created. As such, the modifications that are made are subject to multiple assumptions. It is impossible to know whether the modifications are feasible in the exact systems they are implemented, but the connections created and flow amount estimates are based upon the other UIEs. The other networks provide a good indication of orders of magnitudes and percentages of flows that may transfer from one actor type to another. Further research into each of these systems would be needed to properly understand the feasibility of the modifications. Therefore, the modifications should not be seen as the most realistic or most improved systems. Rather, these modified networks are meant to test the design guidelines outlined. The results of the modified networks will be compared to the original networks to see if the goals were accomplished.

All networks are balanced so that each compartment (actor) has equal imports and exports. This is contrary to the original modeling which took the networks exactly as they were represented, sometimes resulting in unbalanced networks. This is important because it more accurately represents the conservation of mass within each compartment. However, this assumes that there is no storage within each actor, or more accurately, that there is no change in the amount stored within each actor.

7.1.1 Toronto Nitrogen

The original Toronto Nitrogen network (shown in Figure 13) focuses on the nitrogen of food that is imported into the system for human consumption and where this nitrogen is exported. It includes the central actor “Human Bodies” which takes in all imports of nitrogen through available food. This nitrogen is then split into 5 different outputs, 4 of which immediately exit the system. The one remaining output is residential composting that comprises a very small portion (less than 1%) of the total imports to the system. There are three different years analyzed in the previous chapters, all with the structure and only slightly differing flow amounts. The baseline network used for this system is the 1990 network. This network could benefit by enhancing the system due to the following issues. The as is scenario has limited waste recovery (DG2), excludes the processing of waste nitrogen (DG1), and is solely dependent on a single import of food (DG3). The modifications proposed address these shortcomings. The modifications to this network are based on similar, but better performing nitrogen, UIEs, specifically the Central Arizona-Phoenix and Beijing networks. As stated previously, these networks provided basic guidelines for network modification such as the amount of nitrogen needed from the atmosphere to sustain a specific amount of agriculture. Table 24 shows the modifications proposed, which design guideline they address, and the reasoning behind that modification. There are three primary modifications that comprise one scenario (modified 1), and an additional modification that is added to these three to create an additional scenario (modified 2). The primary modifications are meant to represent a change in the model to represent the network more accurately. The final modification is an improvement that could be made to the network that would require changing how the network currently operates. Therefore, it was important to separate these two to understand the effects independently. These modified scenarios are shown in Figure 13.

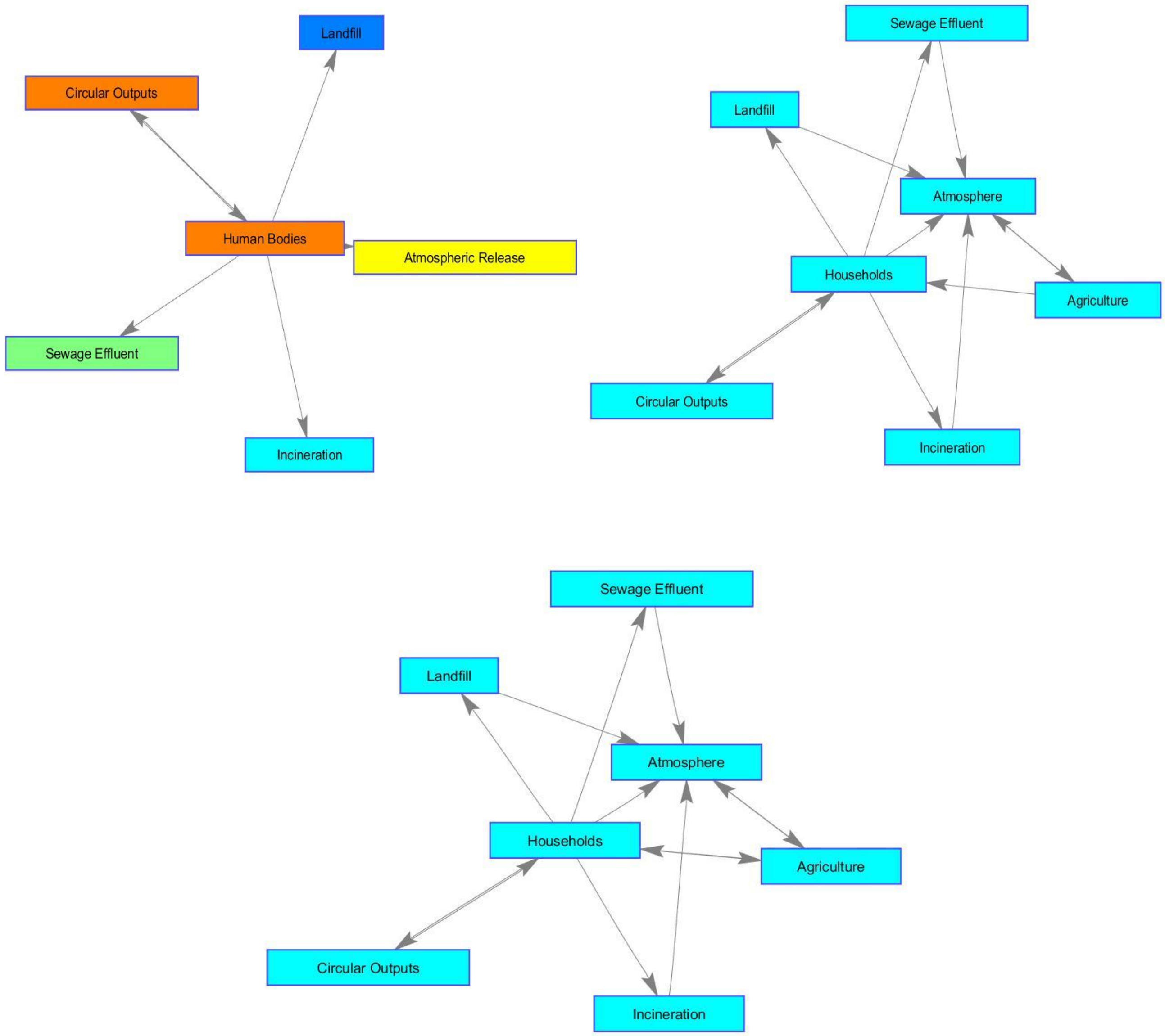


Figure 13 Network configurations for baseline (top left), modified 1 (top right) and modified 2 (bottom) Toronto Nitrogen networks. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Table 24 Suggested modifications to Toronto Nitrogen network with corresponding design guideline and reasoning. The final suggestion (in gray) is for a second modification scenario that adds the final suggestion to the first three modifications.

Modification	Design Guideline(s) Addressed	Reasoning
Renamed Human Bodies to Households	DG1	The actor Human Bodies is too specific and can only encompass the nitrogen transferred from food. By renaming this to households, more flow is encompassed and more connections can be made that include non-food nitrogen. Thus, this better models the system to include all network functions.
Added Agriculture, with 50% of food supply now coming from this actor	DG2/DG3	The sole dependence on imported food creates a potentially brittle system as there is no way to sustain if these imports are eliminated. By putting an agriculture actor into the system, this provides another source of food while also providing an actor to send waste nitrogen to for processing and reintroduction back into the system.
Renamed Atmospheric Release to Atmosphere, 50% of previous exports now go to this actor	DG1/DG2	The atmosphere is critical to the nitrogen cycle. In other nitrogen UIEs, it plays a crucial role in processing and cycling nitrogen. This change treats the atmosphere as it is already functioning while allowing a more granularity of the fate of the flows of the system.
10% of Household nitrogen waste goes to Agriculture actor	DG2	Instead of increasing small scale backyard composting, a greater impact could be achieved if this waste nitrogen could be put back directly into the agriculture of the network. This helps close the loop, while reducing the amount of nitrogen needed from other sources (i.e. fertilizer) to grow food.

Table 25 shows the comparison of ENA metrics between the baseline and two modified networks, while Figure 13 shows the network configuration for the modified network. As seen, the ecological performance is improved across almost every metric. Highlighting a few of these metrics, it can be shown how the modifications interacted with the design guidelines proposed. There is an increase in cycling in the network as shown by the increase in Cyclicity and FCI. More cycles are added to the single cycle previously present, and a far greater amount of the material is now being cycle. While still relatively low (less than 10%), this is a dramatic increase from the baseline scenario. The change in structure to better connect and bring cycles into the network creates a single SCC that encompasses all actors. There is an increase in the MPL, showing that the nitrogen within the network visits more actors before exiting the system, meaning a greater use of this resource. In the baseline network, all actors were specialized predators, but this has decreased with the modifications. Additionally, the number of actors that rely on a single source has also decreased. This should mean a more resilient system.

Table 25 Ecological metrics for baseline and modified Toronto Nitrogen networks

Ecological Metric	Baseline	Modified 1	Modified 2
Cyclicity	1.000	1.785	2.000
Linkage Density	1.000	1.714	1.857
Prey Predator Ratio	0.333	1.000	1.000
Generalization	1.000	1.714	1.857
Vulnerability	3.000	1.714	1.857
Actors	6	7	7
Links	6	12	13
Connectance	0.167	0.245	0.265
Percentage of Connecting Actors	0.167	0.571	0.571
Specialized Predator Fraction	1.000	0.714	0.571
Mutualism Index	0.625	1.450	1.450
Finn Cycling Index	0.002	0.070	0.083
Mean Path Length	1.683	2.044	2.030
Average Mutual Information	1.271	1.069	1.003
ASC/DC	0.430	0.296	0.277
Robustness	0.524	0.520	0.513
Shannon Index	2.955	3.614	3.625
Single Source Percentage	1.000	0.571	0.571
Normalized StDev of AMI	0.136	0.093	0.090
SCC	1	1	1
Actors in SCC	2	7	7

Looking at the information theory metrics, there is not a consistent increase like other metrics, but rather a shift. AMI is decreased in the modified systems, which in this context is a benefit because the network is less constrained. Previously, the flow was extremely constrained leading to a very rigid system, but the modified systems flow more freely. As a result, this leads to a much higher value for DC showing a higher total capacity than before. The system has more room to grow and develop with the new configuration meaning it could be even further improved. Due to the higher DC, the ASC/DC ratio is decreased significantly, but there is a similar value for Robustness. The changes have had the effect of shifting the system from the right side of the Robustness curve focusing on efficiency to the left side focusing on redundancy. That greater redundancy points towards a more resilient system.

In the baseline and modified networks, human bodies/households are one of the most important actors based on the centrality and other metrics. This highlights the importance of this urban actor. In the modified networks, the atmosphere now plays a larger role based on these metrics, similar to the other higher performing nitrogen UIEs. Additionally, the added agriculture actor is now one of the critical actors showing that that an important link was added. Comparing the two modification scenarios, there are minimal differences between the results. The additional modification does create more cycling in the network, but it is not as dramatic of an increase as from the baseline to the first modified network. Additionally, there are even fewer specialized predators with the further modification. This further proves DG2 and the importance of waste recovery, but on top of the other changes it has a smaller effect.

7.1.2 Central Arizona-Phoenix Wastewater Nitrogen

The Central Arizona-Phoenix Wastewater Nitrogen network (shown in Figure 14) is focused on the fate of wastewater nitrogen with the majority of this nitrogen either being exported to the atmosphere or moves into the groundwater. This network, like the Toronto one, has a single source of wastewater that imports into the network for processing. The Wastewater Treatment Plants is the single central actor to which every other actor is connected. This is a linear system with no cycling. As this is a waste treatment network, it is directly related to DG2, but it also lacks the actors further up the waste stream which is related to DG1. As with the previous modified network, these modifications are based upon the other nitrogen UIEs and are shown in Table 26. Specifically, this uses the Toronto network as a guide for how much nitrogen should enter as food to produce the same amount of nitrogen in the wastewater. This was calculated to be a factor of 10.2 meaning for every one unit of wastewater nitrogen, there are 10.2 units of incoming food nitrogen.

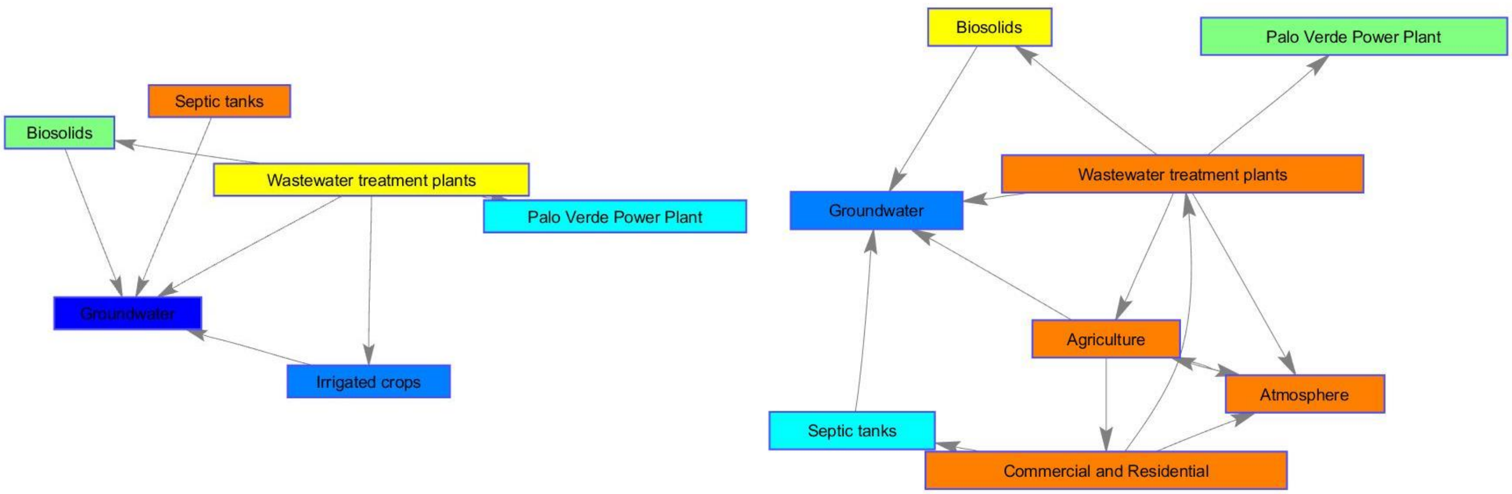


Figure 14 Network configuration for baseline (left) and modified (right) Central Arizona-Phoenix Wastewater Nitrogen network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Table 26 Suggested modifications to Central Arizona-Phoenix Wastewater Nitrogen network with corresponding design guideline and reasoning.

Modification	Design Guideline(s) Addressed	Reasoning
Added "Commercial and Residential" and "Atmosphere" actors	DG1	The Commercial and Residential actor acts as the upstream actor for the wastewater. This is the critical source that is missing from this network but is well within the system boundary. This also allows flows to point back to this actor to complete the loop. This actor takes in nitrogen as food and then sends the waste nitrogen into the existing system. The amount of food taken in is a factor of 10.2 times greater than the amount of wastewater nitrogen as stated previously. The Atmosphere receives the majority of the nitrogen from this network but was not previously included in the baseline network. By adding this actor, it brings this flow into the network instead of exporting it and allows for more interactions, such as with agriculture.
Renamed "Irrigated Crops" to "Agriculture," with 50% of required food coming from this actor	DG2	Similar to the Toronto network, it was important to provide a source of food inside the system. Crops were already in the system, but with the added Commercial and Residential actor this nitrogen can now have a complete loop. This actor also provides a significant portion of the needed food. It acts in the decomposer role, upcycling nutrients that would otherwise exit the system.

Table 27 shows the ENA results for the baseline and modified system. Additionally, Figure 14 shows the network configurations for these two networks. With the modifications, this network now includes cycling as shown by the increase in Cyclicity and FCI. The amount of nitrogen cycled is also a large amount with the FCI being close to the maximum seen for UIEs. In the baseline case, none of the actors acted as connecting actors, but in the modified network over half are on a path between two other actors. This is also seen in the increase in MPL with more actors being visited by the flow before exiting. Both point to greater resource utilization and a more connected network. There is less reliance on single sources and fewer specialized predators, meaning a less vulnerable network. The Robustness increases a considerably, and the network shifts on the Robustness curve from efficiency to redundancy. Wastewater treatment plants are still largely important in this modified network. This does not fundamentally change the focus of the network, but the added Agriculture, Commercial and Residential, and Atmosphere actors all play a large role as well whereas previously they were not present. Specifically, adding Commercial and Residential is the effect of adding the urban actor into the network and this actor has the highest centrality for 3 of the 4 indices meaning it is critical to connecting the network together. By including the appropriate actors, the network performance increases meaning this is a better performing network than initially thought. This shows the need for all systems to be properly modeled.

Table 27 Ecological metrics for baseline and modified Central Arizona-Phoenix Wastewater Nitrogen networks

Ecological Metric	Baseline	Modified
Cyclicity	0	1.618
Linkage Density	1.167	1.750
Predator Prey Ratio	1.000	0.750
Generalization	1.750	1.750
Vulnerability	1.750	2.333
Actors	6	8
Links	7	14
Connectance	0.194	0.219
Percentage of Connecting Actors	0	0.625
Specialized Predator Fraction	0.750	0.625
Mutualism Index	1.000	1.370
Finn Cycling Index	0	0.117
Mean Path Length	1.394	1.764
Average Mutual Information	1.314	0.943
ASC/DC	0.603	0.307
Robustness	0.440	0.523
Shannon Index	2.181	3.071
Single Source	0.833	0.500
Normalized StDev of AMI	0.134	0.133
SCC	0	1
Actors in SCC	0	4

7.1.3 Combined Toronto and Central Arizona-Phoenix Wastewater

As mentioned, the Toronto nitrogen network focuses on food imported into the network via human consumption and the fate of waste nitrogen after that consumption. This network lacked in showing how that waste nitrogen is processed. In a similar but opposite wat, the Central Arizona-Phoenix Wastewater nitrogen network shows in detail the processing of the waste nitrogen, but it starts with wastewater and does not show the upstream human consumption or food production. Therefore, these networks were combined and modeled together to complement one another and create a network that included a nitrogen network from food production to final waste processing. This combined network takes the previously two modified networks and combines them by eliminating repeated actors. As a result, the combined network is an 11 actor network encompassing the import and production of food and the processing of waste nitrogen from an urban area. The ENA results for this are shown in Table 28, with an updated network diagram in Figure 15. This network diagram can be compared to the baseline networks shown in Figure 13 and Figure 14. The results show similar ecological performance to the two previously modified networks. No values are dramatically different, so all the analysis previously stated holds true for this network as well. These results are also very similar to the Central Arizona-Phoenix nitrogen network which has 10 actors and 22 links. By combining the modifying two other networks, it was possible to generate a network that performs towards the top of the UIEs. This makes sense as it includes many of the same actors and has similar proportions of flow going to those same actors. This network includes more cycling with greater redundancy and a decrease in single source reliance when compared with the baseline cases. The Agriculture and Household actors are two of the most critical/central as would be expected from previous analysis. In general, all three of these modified nitrogen networks accomplish the same goals. 1. There is a decreased need for outside nitrogen to be imported into the system. 2. There is less nitrogen that is being exported out of the system. 3. By fully modeling all of the interactions that are present, it more accurately demonstrates how these networks function.

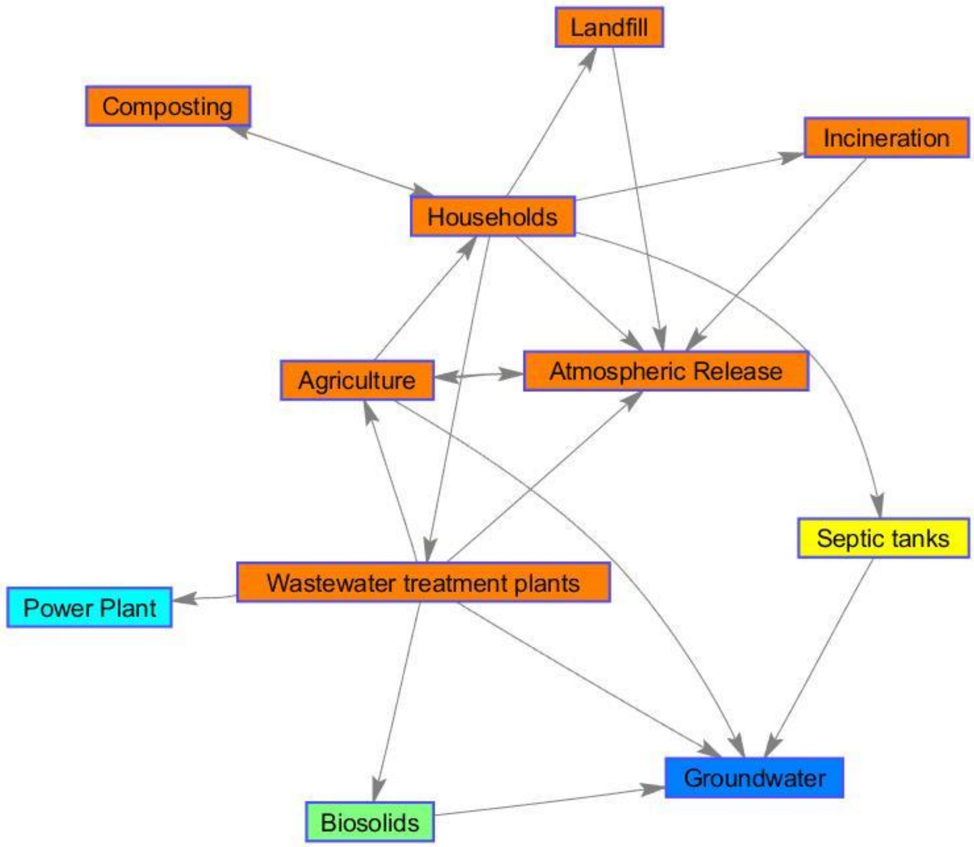


Figure 15 Combined and modified Toronto and Central Arizona-Phoenix Wastewater Nitrogen networks. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Table 28 Ecological metrics for baseline and combined Toronto and Central Arizona-Phoenix Wastewater (CAP WW) Nitrogen networks

Ecological Metric	Toronto Baseline	CAP WW Baseline	Combined Network
Cyclicity	1.000	0	1.899
Linkage Density	1.000	1.167	1.818
Predator Prey Ratio	0.333	1.000	0.818
Generalization	1.000	1.750	1.818
Vulnerability	3.000	1.750	2.222
Actors	6	6	11
Links	6	7	20
Connectance	0.167	0.194	0.165
Percentage of Connecting Actors	0.167	0.000	0.455
Specialized Predator Fraction	1.000	0.750	0.636
Mutualism Index	0.625	1.000	1.161
Finn Cycling Index	0.002	0	0.071
Mean Path Length	1.683	1.394	2.081
Average Mutual Information	1.271	1.314	1.116
ASC/DC	0.430	0.603	0.302
Robustness	0.524	0.440	0.522
Shannon Index	2.955	2.181	3.688
Single Source	1.000	0.833	0.636
Normalized StDev of AMI	0.136	0.134	0.088
SCC	1	0	1
Actors in SCC	2	0	7

7.1.4 Swiss Lowlands Timber

The Swiss Lowlands Timber network is a 6 actor network encompassing the production and consumption of timber and paper. Given the very specific nature of this network, it is not able to be as modified as some of the other UIEs. Instead of adding actors like the other modified networks, the focus of this modification will be on the recycling loops (DG2). The source for this included three different networks with varying levels of timber/paper use and recycling of old timber. The baseline case used for the modification is the same as the original source which is the 1990 flows for the region. The two other networks were attempts to increase the self-sufficiency (or in other words the resilience) of the baseline network. The baseline network configuration is shown in Figure 16.

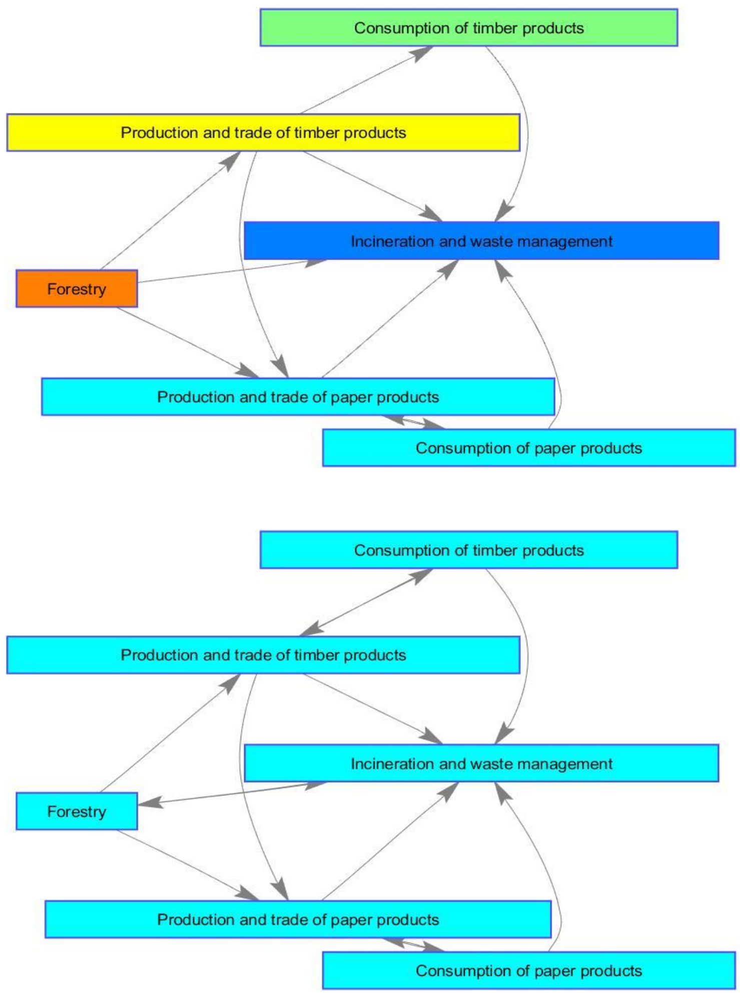


Figure 16 Network configuration for baseline (top) and modified (bottom) Swiss Lowlands Timber network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

There are two modifications that are made to this network, both of which address the issue of waste recovery and recycling. The first is the inclusion of a minor feedback look between the production and consumption of timber products. This modification is included in one of the scenarios in the original source, and a similar value is used for this flow. The second modification is a major recycling loop that connects the Incineration and Waste Management actor back to the Forestry actor. This takes 50% of the exports from incineration and puts it back into Forestry. The ENA results for this modification are shown in Table 29 along with the baseline network and the two scenarios presented in the original source. By comparing to the networks that attempt to increase self-sufficiency, this allows these guidelines to be compared with modifications with a different design goal. Compared to the baseline, the two additional links in the network significantly increase the ecological performance. There is a large increase in both Cyclicity and FCI due to the major feedback loop added. FCI more than doubles meaning more than double the amount of material is being cycled within the system. Due to this change in the cycling, all of the actors are now a part of a single SCC allowing the material to flow between all actors along some path. This has the result of decreasing AMI as the network is less constrained than previously. This decrease in constraint moves the network away from efficiency and increases the Robustness metric, although it still falls on the left side of the Robustness curve. This means the network still leans towards efficiency and theoretically should not suffer economically as a result.

Table 29 Ecological metrics for baseline Swiss Lowlands Timber network compared to modified network and scenarios from original source. Scenario 1 is described as an increase the paper consumption in the network to twice the amount while introducing a feedback loop between the production and consumption of timber products. Scenario 2 is described as an increased use of timber in the construction of buildings and increased recycling rate of 100% for old timber.

Ecological Metric	Baseline	Scenario 1	Scenario 2	Modified
Cyclicity	1.000	1.000	1.000	1.955
Linkage Density	1.833	1.833	1.833	2.167
Predator Prey Ratio	1.000	1.000	1.000	1.000
Generalization	2.200	2.200	2.200	2.167
Vulnerability	2.200	2.200	2.200	2.167
Actors	6	6	6	6
Links	11	11	11	13
Connectance	0.306	0.306	0.306	0.361
Percentage of Connecting Actors	0.333	0.333	0.333	0.667
Specialized Predator Fraction	0.600	0.600	0.400	0.500
Mutualism Index	1.118	1.118	1.400	1.571
Finn Cycling Index	0.152	0.378	0.164	0.331
Mean Path Length	3.758	5.261	3.132	4.213
Average Mutual Information	2.000	2.174	1.811	1.725
ASC/DC	0.580	0.671	0.517	0.471
Robustness	0.456	0.386	0.492	0.512
Shannon Index	3.448	3.240	3.501	3.663
Single Source	0.667	0.667	0.500	0.333
Normalized StDev of AMI	0.068	0.065	0.063	0.062
SCC	1	1	2	1
Actors in SCC	2	2	4	6

The Incineration and Waste Management actor is still the key actor in the system, but even more so in the modified network as it plays the key role to recycle material back into the system. Comparing to the other two scenarios proposed by the original authors, there are some similar increases in ecological performance shown. In Scenario 1, there are larger increases in MPL, FCI, and AMI, while in Scenario 2 there is a larger increase in Robustness and less reliance on single sources. This modified network, as proposed by the design guidelines, seems to hit the balance between the other two scenarios with the highest Robustness and cycling values.

7.1.5 Conclusions of Modified UIEs

Across all of the modified UIEs, ecological performance was improved by using the design guidelines suggested. The modifications allowed these lesser performing networks to be brought up closer to the UIEs with higher ENA metric values. By building out complete networks with impactful additional links, cycling was increased, there was a reduction of single source reliance, and more flow was kept inside the systems. One interesting result was the reduction in AMI in all of the modified scenarios. This means that all modified scenarios became less constrained, thus moving away from efficiency towards more redundancy. Human designed systems often time prioritize efficiency, as shown here, and these design guidelines shift these systems to have more built-in buffer to respond to perturbation. Additionally, across the modified nitrogen networks, the central actor is always households/urban area. There is a clear need to include this actor any time a nitrogen network is modeled as it has the most influence as indicated by these metrics.

7.2 Automotive Production

One of the case studies of this dissertation is that of an automotive manufacturing plant and the corresponding network, which is based around a real automotive manufacturing plant located in northwest South Carolina. With that said, this is a theoretical network, and many assumptions are still made due to lack of information around every aspect of that plant. To model this network, it was first important to identify the actors/components of the automotive production network. While the central focus of this network is the plant itself, there are several other components that support and interact with it and that are important to understand the greater network. These components also allow for modifications of the network to test the proposed design guidelines.

The main actors as well as what they consume and produce are given in Table 30. Non-local components such as suppliers are not actually in the network and act as either importers into or exporters out of the network. As shown, this system is primarily focused on the actors that are co-located as is true for all natural ecosystems. There is some level aggregation that occurs within these actors, which is necessary for modeling purposes, but it does not obscure the connections that are present. However, in this theoretical network, these is assumed to be a single instance of the major infrastructure actors (landfill, power plant, water supply, etc.). Additionally, some of these actors may not have a current connection with the automotive manufacturing plant (such as agriculture), but the modifications look to bring all of these actors into connection with one another through direct or indirect paths.

Table 30 Automotive production actor roles

Actor	Consumes	Produces
Assembly Plant	Raw material Automobile components Energy Water Food Ancillary products	Vehicle Waste
Local Suppliers/Industry	Raw material Energy Water Food Ancillary products	Automobile components Waste
Non-Local Suppliers Residential, Workers, Consumers	Raw material Vehicle Energy Water Food	Automobile components Waste
Agriculture	Energy Water	Food Waste
Landfill	Waste	Landfill gas
Recyclers	Waste	Raw material Ancillary products Waste
Energy Supplier	Raw material	Energy Waste
Water Supplier/Treatment	Waste Water	Water

7.2.1 Model Assumptions

To facilitate the modeling, the following assumptions were made with respect to a potential automotive ecosystem structured around an automotive manufacturing facility. These assumptions help to bound the system and realistically constrain potential additional actors and connections, and partially reflect some specific attributes of this plant that might not be true for other production facilities. Specific aspects of this plant are the presence of an onsite wastewater treatment facility that handles industry specific containments and a large onsite retention pond that is not currently in use. There is a small solar power array that provides minimal energy to the automotive plant.

Agriculture represents a broad range of things that are produced locally. This could include any of the following: food from home gardens that people bring into work, food from a community garden onsite at the automotive plant or another local company, local crops, tree farms, food from a farmers market. It is assumed that these products are consumed locally in some capacity and therefore stay in the ecosystem.

All recyclers are assumed to be local and are therefore consuming local resources. These recyclers may in actuality be onsite at the plant or a local supplier, but they are treated as a separate actor. In the closed loop recycling system, it is assumed that the products created by these recyclers are consumed directly by the actors that are supplying the initial waste to be recycled.

Some actors are included in the baseline model that are not initially connected to the network. These actors exist physically but are not currently being utilized and are included so they can be used in the modified scenarios. For example, the onsite pond is included in the baseline water network even though it is not connected to the baseline network in any way, but it could be used to provide additional water to the plant assuming the infrastructure was added for this.

The residential actor represents the people that live in the ecosystem and includes the workers at the manufacturing plant and the other local suppliers as well as the consumers that are purchasing vehicles. As is known, the majority of vehicles are not sold locally, but it is assumed at least some will so this actor is the consumer of product produced by the assembly plant. This actor represents the interactions these people have while outside of work, i.e. at home, eating out, shopping, etc.

Local is loosely defined for this system and is assumed to be anything that is drawing from the same resource pool. These resources include food, water, and energy. It is assumed these actors are connected through some form of infrastructure and could easily exchange flows.

Suppliers are grouped into local and non-local categories. Considering the number of suppliers for these vehicles, the suppliers would dominate the food web in terms of number of actors. Therefore, it is assumed the suppliers can be grouped together. This means that the connection between suppliers and the assembly plant represents a wide range of materials, products, shipping methods, etc. In this context, all of the suppliers are acting the same in that they are taking in some external materials and supplying the assembly plant with an automotive component.

7.2.2 Structural Modeling of Automotive Manufacturing

The system is modeled structurally first to begin to understand the network and potential for modification. This provides a network that is simpler and easier to modify while still providing insight into the system functionality. To further discretize the network, the automotive ecosystem is broken into three main networks that have distinct flows and characteristics. These three networks are water, material, and energy. For each network type, there will be various improvement scenarios explored. These networks are all connected to one another, but will be analyzed separately initially to see what sort of impact a number of selected modifications to the individual networks will have. The final analysis will combine all of these networks together to create the overall automotive ecosystem. This analysis will present the ideal automotive ecosystem considering all suggested improvements to the individual networks. While the combined network will include all components of the ecosystem, each individual network type will only include the actors relevant to that flow. For example, the water network would not include the landfill actor as there is no water flow to or from this component.

7.2.2.1 Water Network

Automotive production is a water intensive process and as such the water network is a crucial component of the ecosystem. The water network here is simplified to include the main actors in the immediate area near the assembly plant. In the baseline water network, as shown in Figure 17, water flows from the municipal reservoir and is distributed from there. The onsite automotive manufacturing wastewater treatment filters out the contaminants more specific to the automotive industry, but this water is still sent to the municipal wastewater treatment facility for full treatment. In addition, all other water from the local actors is sent to the municipal wastewater treatment facility and redistributed through the municipal system so there is some degree of cycling. However, this is assumed to be a relatively small amount compared to the total amount of water flowing through the system which is shown more when flows are added to this network in Section 7.2.3.2. Additionally, there is still a sole dependence on the municipal supply, with no back up reservoir or potential to tap into another source if needed. Therefore, this network could benefit from greater wastewater recovery (DG2) and the inclusion of another water source or water reserve (DG3). Also, by including the residential and agriculture actors, there is greater potential for network connection that expands beyond the manufacturing plant (DG1). From this understanding of the system, three modification scenarios are proposed.

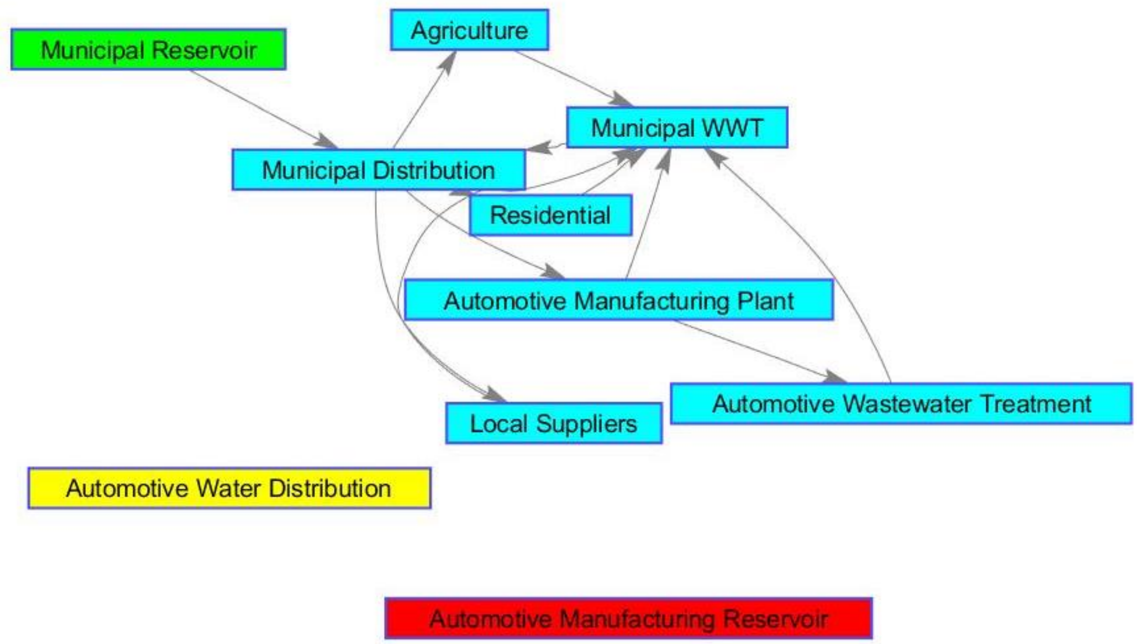


Figure 17 Network configuration for baseline automotive production water network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Rainwater Capture – This scenario (shown in Figure 18) takes advantage of rain capture at the automotive manufacturing plant. The plant would capture the water and store it for onsite distribution. This storage could be the onsite retention pond, or water storage tanks could be installed. Captured water could be used directly in certain parts of the plant such as the restrooms. The onsite wastewater treatment facility could be modified to treat this water for use in the processes that require more refined water. Rain capture could be utilized at any plant, but the quality of the rainwater may vary between locations. A plant located in an area of heavy pollution may have to treat the water to a greater effect before it can be used. Any rain that can be captured and treated reduces the amount of water needed from the municipality thus decreasing water consumption costs. Additionally, the provides the plant with another source of water, reducing the impact if the municipal supply is disrupted for any reason.

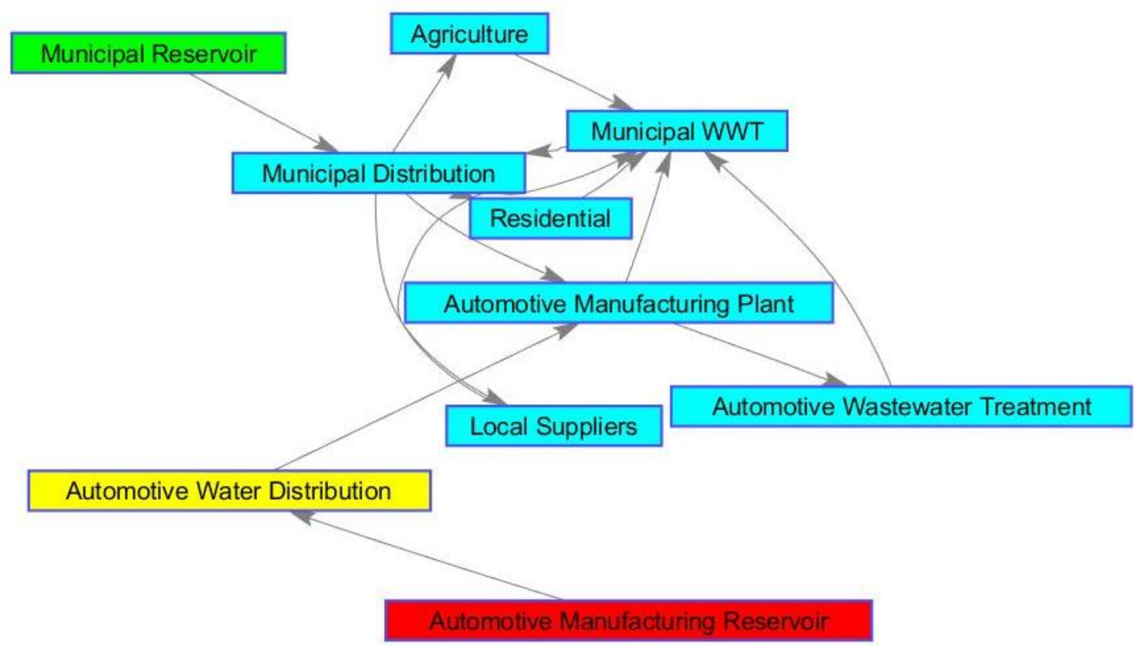


Figure 18 Network configuration for rainwater capture automotive production water network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Gray Water Treatment – This scenario (shown in Figure 19) treats grey water from the plant and uses it elsewhere in the plant. For example, the gray water, after treatment, could be used for the cooling towers. This assumes the onsite water treatment can be modified to treat this water properly. Even without this modification, some water could be used directly without treatment. Gray water usage could be implemented in any plant, regardless of location. Similar to the rainwater capture scenario, this reduces the need for water from the municipal supply, as well as adding another cycle within the network.

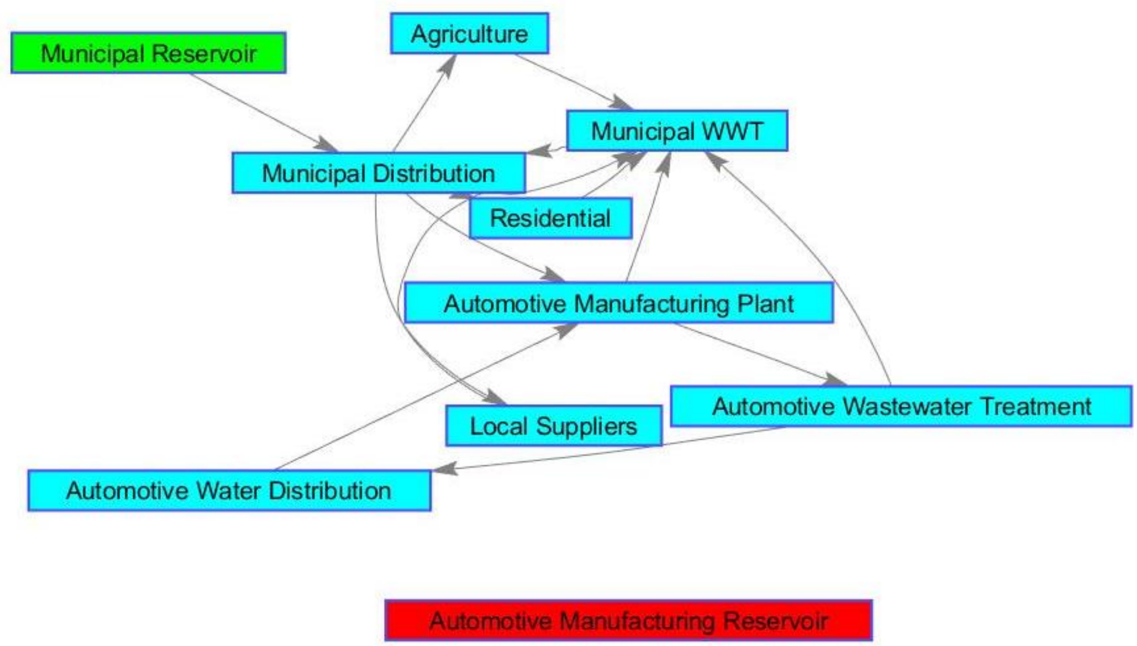


Figure 19 Network configuration for gray water treatment automotive production water network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Community Oriented Network Expansion – This scenario (shown in Figure 20) combines both the rainwater capture and grey water usage scenarios with additional water distribution from the assembly plant to other parts of the ecosystem, including the local community. The automotive plant would capture rainwater, treat it, and send it to the surrounding area for usage. This utilizes the onsite wastewater treatment that would be able to adequately treat the water for municipal use. This is the least realistic of the modification scenarios as it assumes infrastructure for water distribution from the plant, but it also has the largest impact. Not only are more cycles created, but a major second supplier of water is added to the network.

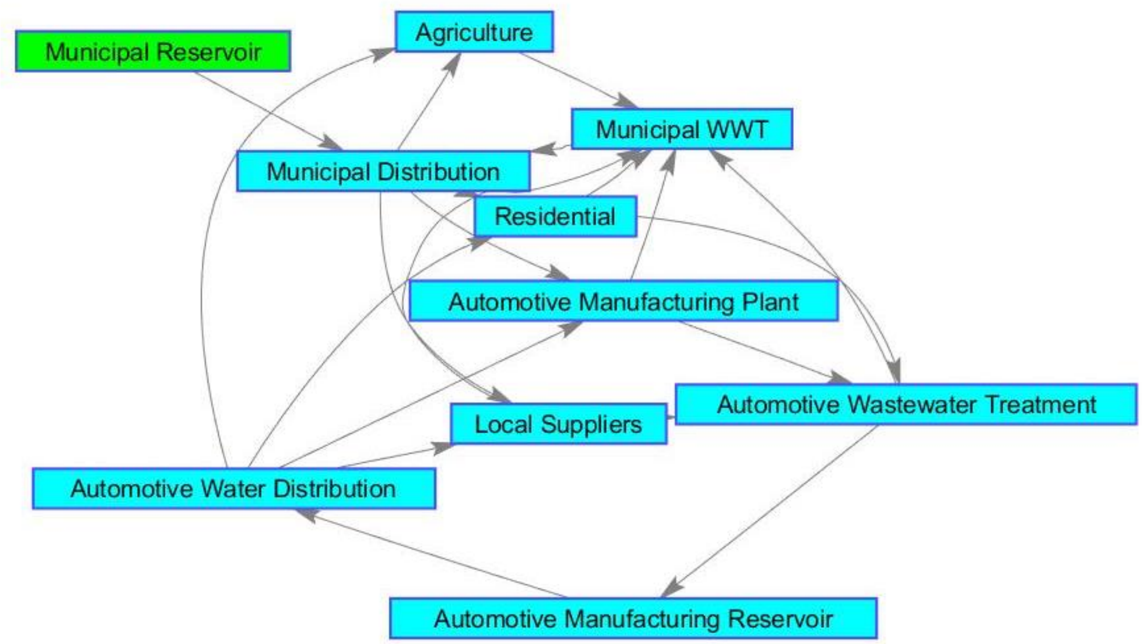


Figure 20 Network configuration for community oriented automotive production water network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

The resulting ENA values for the different water networks described are given in Table 31. As can be seen, even though the number of actors remains the same, cyclicity is improved, as well as the number of links in each network compared to the baseline water network. The community-oriented expansion scenario has the greatest increase in metrics, especially Cyclicity. The rainwater capture scenario is only a slight improvement over baseline, with the gray water treatment scenario being intermediate between the two other scenarios.

The improvement in the resilience (i.e. redundancy) of the system is suggested by the decrease in the Specialized Predator Fraction, which is improved significantly in the community-oriented modification scenario. Across the networks, the municipal water supply is the most central to the network based on the centrality indices. However, in the community-oriented network, the automotive plant supply of water is the second most central. Although it does not provide water to as many actors, it still acts as a new critical link within the system. The modifications improve the number of actors involved in a SCC slightly by now including the plant and its water distribution system. All of these scenarios will be examined further when flows are added in the next section.

Table 31 Structural ecological metrics for baseline and modified automotive production water networks

Ecological Metric	Community Oriented Expansion	Grey Water Treatment	Rainwater Capture	Baseline Water Network
Cyclicity	1.924	1.708	1.663	1.663
Linkage Density	2.000	1.400	1.400	1.200
Prey Predator Ratio	1.111	1.125	1.250	1.143
Generalization	2.222	1.750	1.750	1.714
Vulnerability	2.000	1.556	1.400	1.500
Actors	10	10	10	10
Links	20	14	14	12
Connectance	0.200	0.140	0.140	0.120
Specialized Predator Fraction	0.222	0.625	0.625	0.714

7.2.2.2 Material Network

The material network consists of the vehicle components, packaging, office supplies, food, and all other miscellaneous materials that are used in the production of the vehicle, including resources used by the plant workers. The main actor in this ecosystem is the assembly plant, and as such, there is not a large consumption of raw materials in the assembly of the vehicles. Instead, there is a much larger concentration of fabricated components and packaging. This may vary greatly depending on the exact configuration of the plant being analyzed. Some plants may consume a larger amount of raw material and have more process waste. Due to the structural matrix not including a row for imports, "Non-Local Suppliers" are shown in this network. The baseline material network, shown in Figure 21, consists of many things flowing to the assembly plant with little cycling of the material within the ecosystem. Recycling occurs, but it is assumed the majority of this material does not end up back in the system. The modifications to this network look to increase the recycling (DG2), while also modeling the interactions that occur outside the plant (DG1). Additionally, by modeling the system to include specific recyclers instead of an aggregated recycling actor, more connections can be made for greater network performance. There are two modification scenarios shown.

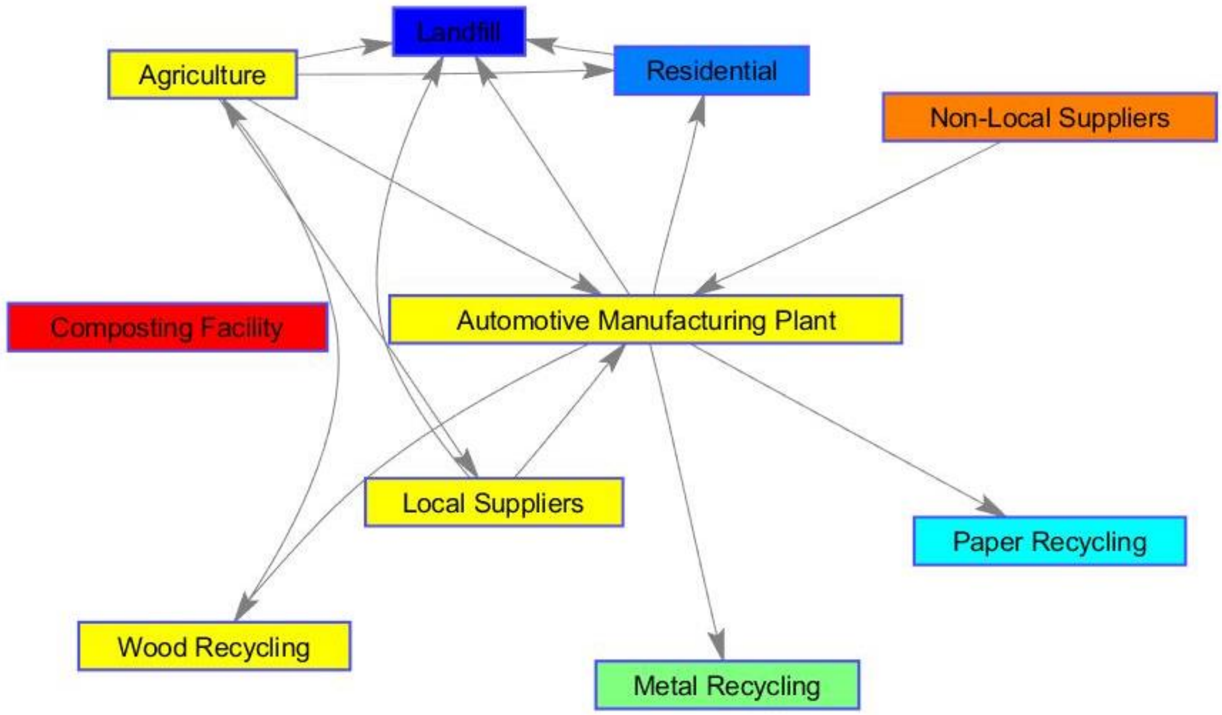


Figure 21 Network configuration for baseline automotive production material network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Increased Recycling – This scenario (shown in Figure 22) consists of much more recycling than the baseline case, but still assumes that most of this recycling does not enter back into the system. The increase in the recycling is due to the addition of other actors participating in recycling including the residential actor and other local suppliers. This adds importance to these actors, while creating more loops.

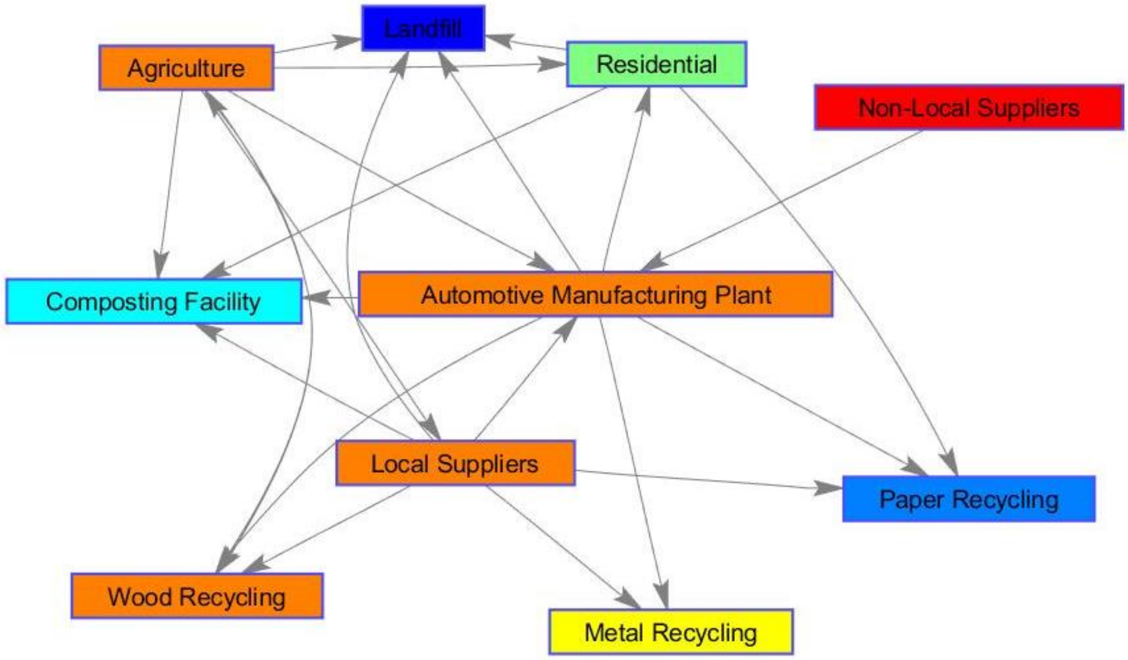


Figure 22 Network configuration for increased recycling automotive production material network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Closed Loop Recycling – This scenario (shown in Figure 23) introduces closed loop recycling where the recycled material is utilized directly by the actors in the system. This takes the increased recycling to the next level by assuming that recycled material stays within the network. This should show the importance of keeping material contained within the network as opposed to exporting upcycled material to be used elsewhere. In this way, these actors function much more as decomposers that provide benefit to the system as opposed to waste dumps.

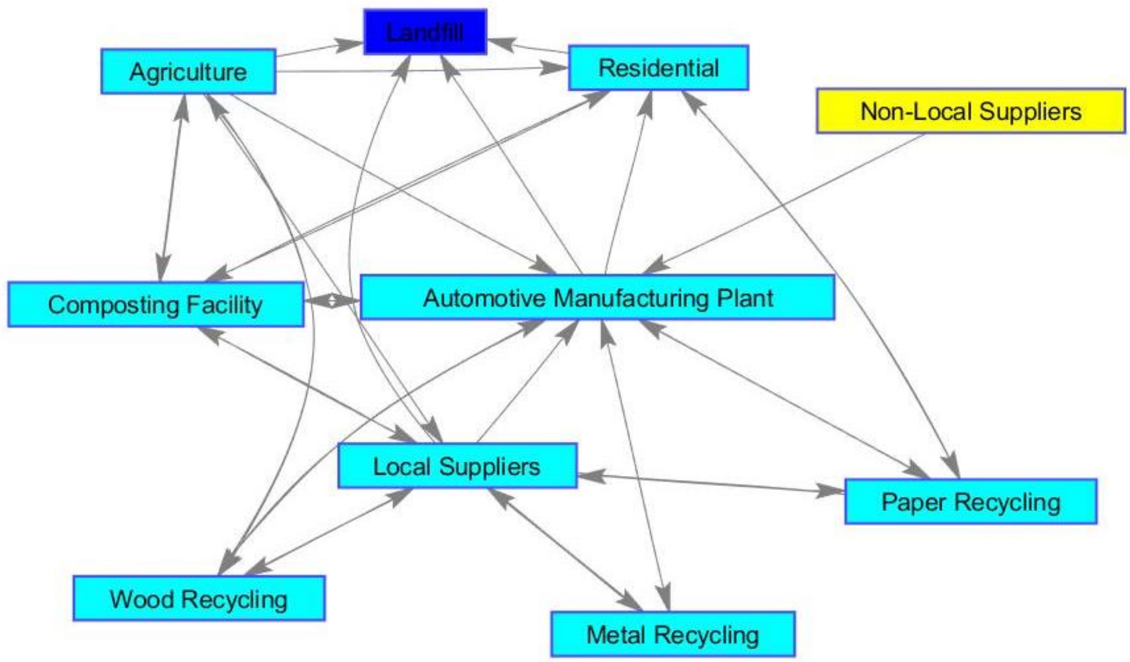


Figure 23 Network configuration for closed loop recycling automotive production material network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

The ecological metric values for the different material networks described are given in Table 32. In both of the modified scenarios, there are improvements across the ENA metrics. By sending more material to the recyclers, additional loops are created as seen in the increase in Cyclicity in the increased recycling scenario. However, by creating closed loop recycling, the cycling is increased substantially more. The number of links is more than doubled from the baseline. Additionally, the Specialized Predator Fraction is dropped to zero in the closed loop recycling modification meaning every actor has multiple sources from with to feed. The increased recycling scenario improves this as well, but not as much.

The central actor remains the automotive manufacturing plant in all scenarios, but the importance of the landfill is decreased in the increased recycling scenario and even further in the close loop recycling scenario. The relative rank of the residential actor based on centrality indices remains constant. The closed loop recycling scenario brings all but two actors (landfill and non-local suppliers) into the SCC meaning the material has many more pathways to flow. It must be noted that these flows are of different material (food, metal, etc.) so while the structure may show these increased metrics, the flow analysis would be altered due to needing a common currency for that analysis. With that caveat, this still shows the potential for improvement compared to the baseline.

Table 32. Structural ecological metrics for baseline and modified automotive production material networks

Ecological Metric	**Closed Loop Recycling**	**Increased Recycling**	**Baseline Material Network**
Cyclicity	3.704	1.618	1.221
Linkage Density	3.400	2.300	1.400
Prey Predator Ratio	1.000	0.667	0.750
Generalization	3.778	2.556	1.750
Vulnerability	3.778	3.833	2.333
Actors	10	10	10
Links	34	23	14
Connectance	0.340	0.230	0.140
Specialized Predator Fraction	0	0.222	0.625

7.2.2.3 Energy Network

The energy network discussed and analyzed in this section is a simplified representation of the energy-related actors in an automotive ecosystem. This generalizes the energy in the ecosystem to include a number of different flows. The Energy Center consists of all onsite electricity generation, hot water production, and chilled water production. This includes two gas generators with cogeneration capabilities, a natural gas boiler, centrifugal chillers (electric), and absorption chillers (hot water).

In the baseline case, the plant utilizes a number of different energy sources and conversion agents. New energy is supplied primarily by grid electricity and utility and landfill gas, although small amounts of hydrogen gas and photovoltaic (PV) generated electricity also are included. The baseline energy network is given in Figure 24. Energy in the form of hot and chilled water are also included in this network. Due to the nature of energy, it is not easily cycled or recycled as is the case with water or material. Most of the focus of the modifications focus on increasing the number of sources for the different forms of energy (DG3). This can only be accomplished by making separate actors for the different components that provide the different sources of energy (DG1). These modifications utilize various technologies that act in the decomposer role by taking an input and upcycling it to make it useful to the system once again.

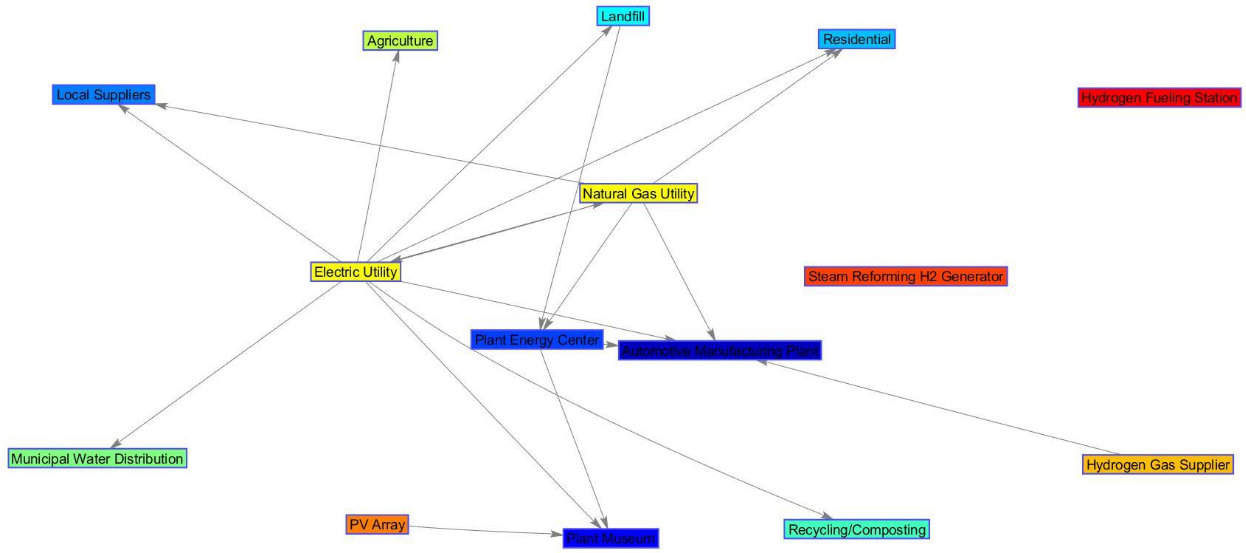


Figure 24 Network configuration for baseline automotive production energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Hydrogen Generation – The automotive manufacturing facility uses hydrogen to power its forklifts and delivery carts. Allowing the plant to produce its own hydrogen would improve the functional diversity of the system and allow the plant to be organized more like an ecosystem by allowing it to cycle energy from multiple actors. Hydrogen that is normally purchased from an external supplier is replaced with landfill gas processed into hydrogen using steam reforming of methane. This is a common process and the required equipment is commercially available. This adds another source of this critical resource, increasing the resilience (i.e. redundancy) of the system. This scenario (shown in Figure 25) is explored more in the following section where the flow is incorporated.

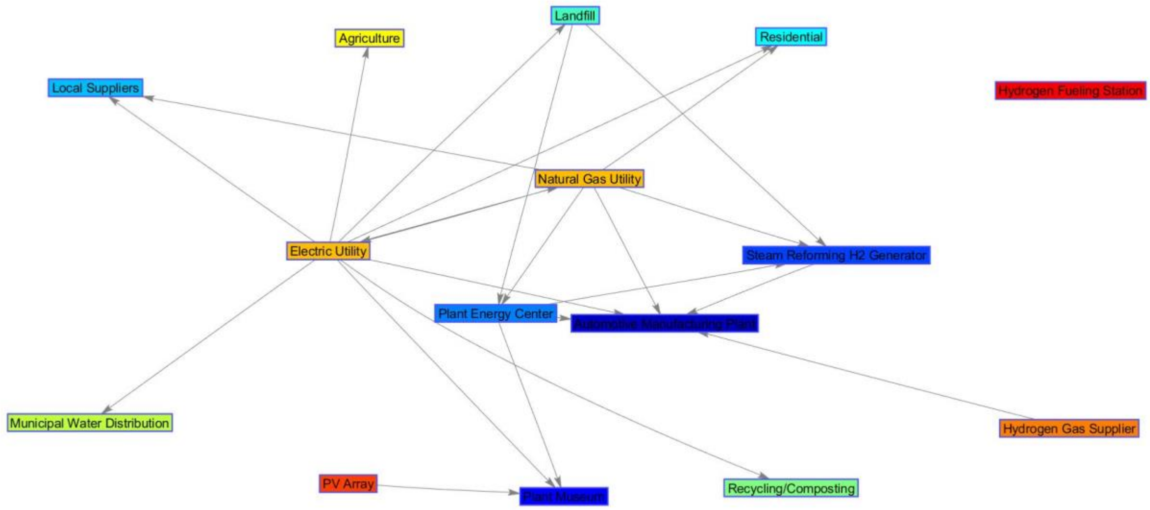


Figure 25 Network configuration for hydrogen generation automotive production energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Microgrid – Incorporating the automotive plant into a microgrid with the surrounding community would increase the diversity of power of the surrounding community, making the area around the plant more like an ecosystem. Microgrids allow a small community (be it industrial or residential, or both) to self-sustain during power outages caused by grid maintenance, disasters or energy supply issues. The automotive plant could take the natural gas produced by the nearby landfill and make its generated electricity available to critical infrastructure such as police and fire stations, communication centers, hospitals, and gas stations. A variety of actors within a 10-mile radius that could potentially participate in a microgrid, including an airport, a hospital, police departments, and several gas stations. Beyond electricity, a shared hot water network would allow the automotive plant to share the hot water from the cogeneration equipment during an outage situation. During severe winter weather, heating is a crucial resource, especially in hospitals or for more vulnerable residents. Similar to the community-oriented water network, this allows the plant to be a source of energy instead of just a consumer. The network configuration for this is shown in Figure 26.

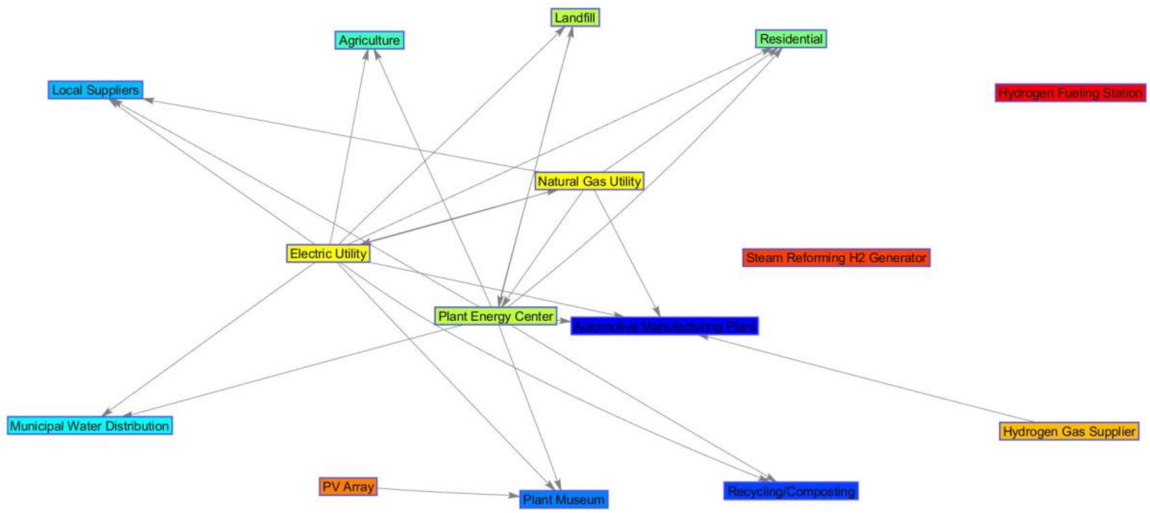


Figure 26 Network configuration for microgrid automotive production energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Expanded Solar Capacity – The current PV array is limited in scope, only being connected to the museum portion of the plant. An expanded PV system could contribute to the electricity needs of the manufacturing facility itself. In the event of a power outage, the PV system can support essential factory services along with the onsite landfill gas generators. If the plant were to implement a microgrid setup with the surrounding community, the expanded PV array could assist with external power loads as well. This scenario is shown in Figure 27.

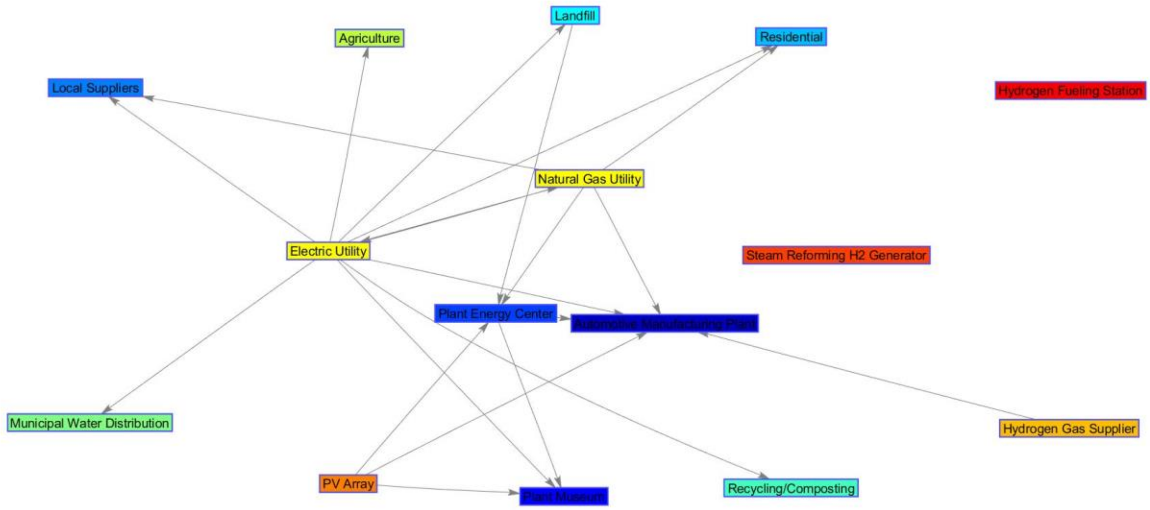


Figure 27 Network configuration for expanded solar capacity automotive production energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Combined – This scenario combines all of the aforementioned energy ecosystem improvements to the automotive production facility: an expanded PV array on the museum, hydrogen generation capabilities through steam reforming, and microgrid capabilities. This represents the ideal case for the energy ecosystem and is shown in Figure 28.

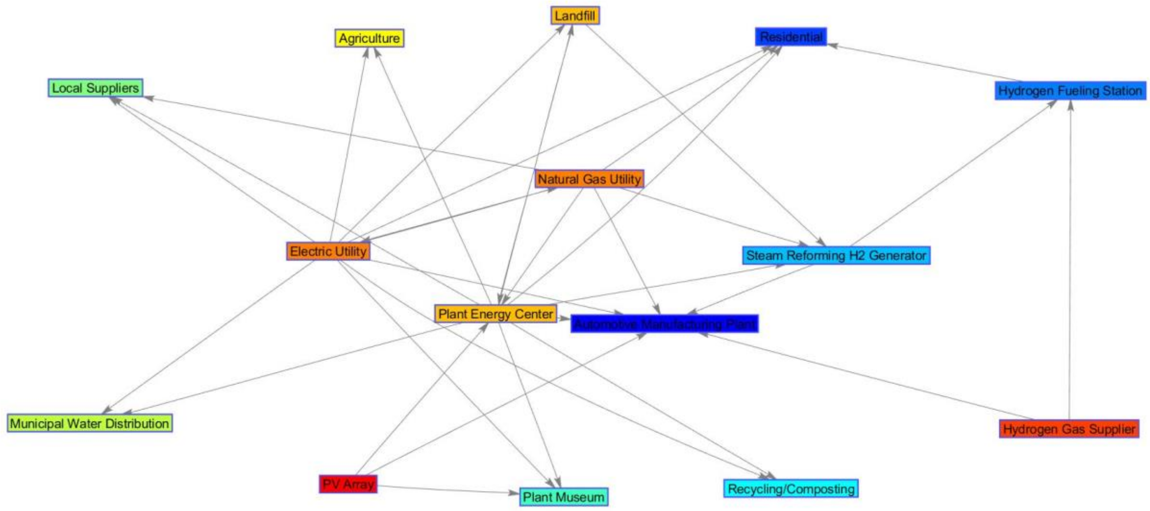


Figure 28 Network configuration for completely modified automotive production energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

The ENA metrics for the different energy scenarios are shown in Table 33. There is no change in cycling, as expected, but many of the other metrics are improved. The number of links almost doubles from the baseline to the combined scenario. This accounts for many of the other increased metrics, but of most significance is the decrease in the Specialized Predator Fraction. Similar to the material and water networks, the modifications improve this drastically, almost eliminating the number of actors that only consume one other actor in the combined scenario. This seems to be most improved by the inclusion of the microgrid, which also has a very small value for this metric. The system should be much more resilient as a result. As would be expected, the central electric utility is the most central actor in the baseline system, followed closely by the natural gas utility. This remains true until the microgrid is implemented, which sees the plant energy center taking a much more central role. In the combined network, the energy center is the most central, overtaking the electric utility. This is typical of energy networks as the suppliers of the energy are connected with all other actors while those actors are not connected to one another.

Table 33 Structural ecological metrics for baseline and modified automotive production energy networks

Ecological Metric	Combined	Microgrid	Hydrogen Generation	Expanded Solar Capacity	Baseline Energy Network
Cyclicity	1.000	1.000	1.000	1.000	1.000
Linkage Density	2.214	1.786	1.643	1.500	1.357
Prey Predator Ratio	0.583	0.545	0.583	0.545	0.545
Generalization	2.583	2.273	1.917	1.909	1.727
Vulnerability	4.429	4.167	3.286	3.500	3.167
Actors	14	14	14	14	14
Links	31	25	23	21	19
Connectance	0.158	0.128	0.117	0.107	0.097
Specialized Predator Fraction	0.167	0.182	0.500	0.545	0.545

7.2.2.4 Water, Material, and Energy Network

The combined network is the combination of the water, material, and energy networks. This combination includes the existing connections in addition to the connections between the networks. These additional connections are primarily due to the use of water and energy of the local actors. A connection in this network can in actuality represent multiple flows that are present between actors. For the combined network, two scenarios are considered. Those two cases are the baseline case, and the fully modified case that represents the ideal automotive ecosystem. This fully modified scenario combines all suggested modifications to the individual networks and combines them into the larger network. Table 34 describes the ecological metric values for these combined networks. The baseline combined network sees the greatest ecological performance of any of the other structural networks because there are inherently more connections between the actors in the system when all systems are combined into one. For the fully modified network, there are almost double the number of links compared with the baseline, and a significantly increased amount of cycling. This results in 18 actors being included in the SCC, an increase from 12 in the baseline case. Unsurprisingly, the most central actor in both of these networks is the automotive manufacturing plant as the network was constructed around it. The second most central actor is the electric utility in the baseline network and the plant energy center in the fully modified network. Although not every actor may process water or material, they all require energy, so this is expected to be central to the network. The waste recovery actors do not change significantly in the centrality ranks.

Table 34 Structural ecological metrics for baseline and modified, combined automotive production networks

Ecological Metric	Fully Modified Network	Baseline Network
Cyclicity	4.366	2.728
Linkage Density	4.217	2.261
Prey Predator Ratio	1.158	1.067
Generalization	5.105	3.467
Vulnerability	4.409	3.250
Actors	23	23
Links	97	52
Connectance	0.183	0.098
Specialized Predator Fraction	0.105	0.067

7.2.3 *Flow Modeling of Automotive Manufacturing*

Although the structure of the automotive ecosystem can reveal much about the capacity for cycling, incorporating flow magnitudes into the analysis enables greater granularity, particularly in terms of the capacity to resist disturbance. However, this analysis requires much information beyond connectivity and limits the number of networks that can be analyzed in this way. This analysis takes some of the previously analyzed structural networks and adds flow magnitudes. With these networks, it is impossible to know the exact flow numbers and as such there are many assumptions and estimates that are made to try and best represent the system. Similar with all flow networks created, these models are not meant to perfectly represent the systems, but rather provide a general idea of how they function with flows within orders of magnitudes as opposed to extremely precise numbers.

7.2.3.1 Hydrogen Flow Network

The use of hydrogen for fuel is one of the most brittle processes within the plant. There is only one supplier of hydrogen and the carts are a critical piece of the assembly process. The entire assembly line would stop if this supply is disrupted. It is estimated that the plant consumes 2,722 MWh of hydrogen annually based on available data (Linde 2010) and assumptions/estimates of vehicle use. The values to get to this annual value are shown in Table 35. This is a very small network as it only encompasses the actors that interact with the hydrogen flow. The primary focus on the modification scenarios is to add a second (or more) source of hydrogen that does not rely on an import to the system. This is directly related to DG3, although it is indirectly related to DG2 as there is some waste or other products being reprocessed into a useful flow/fuel.

Table 35 Values for hydrogen production in automotive production case study

Property	Values
Known Values	
Forklifts and carts	85
Tank Capacity	2kg
Shift Length	8-10hrs
Estimated Values	
Fraction of forklifts and carts in use	0.90
Fraction of H_2 tank used in one shift	0.75
Shifts per day	2
Calculated Values	
Total daily H_2 consumption	230kg/day

Solar Hydrolysis – This scenario proposes using the solar array to power a hydrolysis system that would split water to create hydrogen. The solar hydrolysis process is assumed to be 75% efficient and the current annual solar capacity is assumed to be 157 MWh annually. Using the current capacity, this solar hydrolysis system could account for 4.3% of the hydrogen. This system would use 7,000 gallons of water annually. The current hydrogen supplier would still supply 2,604 MWh of hydrogen per year.

Landfill/Natural Gas – This scenario proposes using a methane steam reforming process to create all of the hydrogen needed by the plant. This process is assumed to be 75% efficient and it is assumed that this process either uses entirely landfill gas or natural gas. This shifts the source of the hydrogen onsite, no longer relying on an importer, but on flow that is already coming to the plant.

Mixture – This scenario proposes using a mix of the other proposed scenarios. It is assumed that 25% of the hydrogen will come from each source. This would mean an increased solar capacity to 907 MWh annually which is almost six times the current capacity. It would require both a methane steam reforming system and a hydrolysis system. The hydrolysis would use 41,000 gallons of water annually. The current hydrogen supplier would still supply 680 MWh of hydrogen per year. This allows for the most sources and should lead to the most resilient system.

With this network, the primary focus is on the resilience. This includes increasing redundancy and the ecological metric Robustness. As such, these results only present the Robustness and ASC/DC values for each network, shown in Table 36. The baseline supply system relies on a single importing actor (supplier) that is responsible for all hydrogen. The calculated Robustness of this system is 0, while the value for ASC/DC is 1 meaning a complete efficient system with no built-in redundancy. The addition of solar hydrolysis increases Robustness but is limited by the amount that could be generated based on the current PV array. The landfill/natural gas reforming scenario increases this further by bringing the sole source inside the network. The final scenario that combines all three new sources has the highest value for Robustness. In each scenario, as more sources are created or more of the hydrogen supply is brough into the system, the system starts to build redundancy and shifts away from efficiency.

Table 36 Robustness and ASC/DC values for baseline and modified automotive production hydrogen networks

Ecological Metric	Baseline Supply System	Solar Hydrolysis	Landfill/Natural Gas	Mixture
Robustness	0	0.2016	0.3747	0.4914
ASC/DC	1	0.8481	0.6841	0.5183

The hydrogen flow analysis is a simple example that only takes into account one flow, but it is important to remember how this fits into the larger energy network. Most of the other energy flows to the plant, which includes natural gas, landfill gas, and electricity, are two orders of magnitude greater than the amount of hydrogen being used. By running the analysis again in the full energy network, the results are quite different. Table 37 shows the same metrics when the different hydrogen scenarios are analyzed in the larger energy network. When these same hydrogen scenarios are analyzed in the larger system, the magnitudes of the other flows drown out the effect of changes to the hydrogen network and these flow metrics are unchanged. This shows the importance of analyzing the hydrogen network separately. The larger system is not affected by the proposed changes, but the robustness of the smaller hydrogen system greatly increases.

Table 37 Robustness and ASC/DC values for baseline and modified automotive production energy networks

Ecological Metric	Baseline	Solar Hydrolysis	Landfill/Natural Gas	Mixture
Robustness	0.5034	0.5034	0.5037	0.5037
ASC/DC	0.4921	0.4921	0.4914	0.4915

7.2.3.2 Water Flow Network

The water network that was analyzed previously with a structurally analysis can be further analyzed by adding the flow amounts. In this updated network, the system is changed slightly in regard to the actors involved and how they are connected based on the available data. The same modifications are considered for this analysis: rainwater capture, gray water use, and a community-oriented network. Given that this now considers flow amounts, these modified scenarios have additional criteria that are outlined below. All of the modifications still address the same design guidelines previously mentioned. The waterflows are estimated from population data, daily water use, and publicly available municipal water data (Greer Commission of Public Works 2017a, 2017b; US Geological Survey n.d.)

Rain Capture – Two cases are considered for the rain capture scenario. The first calculates a feasible amount of rainwater that could be potentially captured and uses this as an additional supply for the plant. This uses the average rainfall in the area (NOAA n.d.) as well as the roof area of the plant (Daft Logic n.d.) to provide an estimated 87.6 million gallons of water to the plant annually when 90% of the rain is captured (Hicks 2008). This accounts for 42% of the 211 million gallons used by the plant. This water is stored onsite in either storage tanks or retaining pond. The second case assumes that all of the plant water demand can be provided by rainwater capture. This is a far less feasible situation but provides a point of comparison for when there are two separate sources of water (municipal supply and captured supply) providing water to two different systems (other municipal customers and the production facility).

Gray Water – Two gray water cases are considered. The first assumes that half of the plant water can be obtained by capturing, treating, and reusing gray water in the parts of the plant where this would be appropriate. This greatly reduces the amount of water needed from the municipal supply, although it still relies on that municipal supply for the main source of water. The second gray water scenario combines the rain capture with this gray water treatment and use. It uses the feasible amount of rainwater capture and supplements this with treated gray water to supply half of the needed water for the plant. This provides both a second source and increased recycling of previously used water.

Community – The final scenario is the same community-oriented modification that was examined in the structural analysis. This case assumes the same amount of rain capture as in the first rain capture scenario, but this water is now distributed to the local actors. This distribution breakdown is set at 10% for Residential, Local Suppliers, and Agriculture, with the remaining 70% staying with the automotive plant. The amount of gray water reused is set so that 50% of the water needs for the plant are provided by the gray water and rain capture system. In this system, there are two separate sources that provide water to all of the actors, which should result in a more resilient system. Additionally, there is more water recycled within the plant.

The ENA results for the automotive water flow network are shown in Table 38. Overall, there is little difference in the metrics across the different scenarios. Compared with the baseline, Cyclicity increases some in the gray water and community-oriented cases but decreases when there is sole reliance on rainwater to supply the plant. Additionally, FCI decreases in all cases compared to the baseline. The Robustness remains fairly constant in all scenarios, although there is a slight increase in the community-oriented network. There is a decrease in Robustness for the 100% rainwater scenario. Although a second source is added in this case, both the surrounding city and the manufacturing plant are now more dependent on a single, more brittle source and therefore are more vulnerable to a disruption of that source. Across all scenarios, the municipal supply of water remains central and impactful based on the different centrality metrics. The shift in results are what was expected, although the size of those shifts was smaller than anticipated. One explanation of those smaller shifts could be the relative size of flows. Similar to when the hydrogen network was placed in the larger energy network, changing these smaller flows around has less impact on the flow-based results than changing a larger flow. In this network, the automotive plant accounts for around 16% of the total water flow in the system. While still on the same order of magnitude as the flows going to the other actors, there is a limitation on how much impact modifying the network around the plant can have.

Table 38 Ecological metrics for baseline and modified automotive production water networks

Ecological Metric	Baseline	Rain Capture	100% Rain Capture	RC and Gray Water	50% Gray Water	Community
Cyclicity	1.540	1.540	1.260	1.654	1.654	1.746
Linkage Density	1.429	1.375	1.250	1.500	1.500	1.875
Prey Predator Ratio	0.857	1.000	1.000	0.875	0.875	0.875
Generalization	1.429	1.571	1.429	1.500	1.500	1.875
Vulnerability	1.667	1.571	1.429	1.714	1.714	2.143
Actors	7	8	8	8	8	8
Links	10	11	10	12	12	15
Connectance	0.204	0.172	0.156	0.188	0.188	0.234
Specialized Predator Fraction	0.857	0.714	0.857	0.750	0.750	0.375
Finn Cycling Index	0.138	0.127	0.098	0.128	0.138	0.128
Mean Path Length	2.115	2.115	2.115	2.116	2.116	2.112
Average Mutual Information	1.653	1.690	1.830	1.702	1.672	1.686
Alpha	0.548	0.543	0.575	0.545	0.551	0.538
Robustness	0.475	0.478	0.459	0.477	0.474	0.481
Shannon Index	3.015	3.112	3.182	3.121	3.034	3.133
Single Source	0.714	0.500	0.750	0.500	0.625	0.125
Normalized StDev of AMI	0.096	0.092	0.077	0.091	0.095	0.092
SCC	1	1	1	1	1	1
Actors in SCC	6	6	4	7	7	7

7.2.4 Conclusions of Automotive Manufacturing Case Study

Through this case study, many different facets of an automotive production facility and the surrounding network have been modeled and modified. The structural analysis reveals a much greater potential for cycling and addition of multiple sources. A critical aspect of all of these networks and modifications is the inclusion of the other local actors. When viewed in a vacuum, the impact of a single manufacturing plant is limited. However, by expanding the network to include the surrounding urban area, agriculture, and other industrial actors, this creates a true UIE that has potential to greatly increase resource utilization and decrease the amount of water, energy, and material that is imported into the system. The flow-based metrics showed less improvement than the structural ones, largely due to the relative size of the flows that were being modified. This shows the limitations of only focusing on a single actor within the larger system. The improvements made to the automotive production plant can certainly increase the resilience (i.e. robustness) of that specific actor, but this can only have so much impact on the bigger network. That said, there is still improvement shown, and this case study and modified networks show how all three design principles can be enacted to increase ecological performance.

7.3 Chinese Steel Manufacturing

Another case study to test design principles is that of a Chinese steel manufacturing facility. This comes from Malone et al. and models water and material flow around a steel plant (Malone 2017; Malone et al. 2018). This network is purely an industrial network and does not include any sort of urban actor. While that strays from this dissertation, it is still an effective case study for testing the design guidelines outlined as they are not limited to UIEs but can be used in all systems to increase performance. Malone constructed the network to be analyzed with ENA and created two major modification scenarios to the system to improve performance. The three networks (baseline and two modified) will be summarized here to include how they fit within the proposed design guidelines.

Baseline – The baseline network includes all of the industrial process plants that are involved in the steel making process. This includes coking, cement, iron, lime, and sinter plants to name a few. This also includes the main infrastructure that is required for the plant such as a water treatment facility and power plant. Additionally, it includes a few downstream uses of the steel such as rolling and ship building. In the baseline, the different components are not collocated and therefore some of the flows are not able to be shared. The flows between the components are converted to a common currency of tons of carbon equivalent to adequately model and analyze the system. The system is modeled to include the many different components of the steel making process (DG1), allowing for the modifications that follow to be possible.

Co-location of Plants – In this scenario, the network is modified to co-locate the construction material making plant and the cement plant with the main steel plant. This has the benefit of using excess slag generated elsewhere in the network by these actors, thus creating a way to process this waste material. In addition, this scenario includes the use of recycled scraps from the ship building, equipment manufacturing, and deep processing industries. This again has the benefit of taking some waste stream and converting it into useable material elsewhere in the system. This scenario primarily addresses DG2 with better waste processing.

Wetlands and Pyrolysis – This scenario includes the modifications from the previous scenario, with the addition of another wastewater treatment source. In this expanded scenario, constructed wetlands are used to treat wastewater generated by the various components of the steel production facility. This water is then put back into the system, creating a closed loop system of water. Additionally, the plants from this wetland are burned in a pyrolysis process to generate fuel for the system. This fuel offsets some of the grid electricity that is purchased by the plant. Similar to the first scenario, this addresses DG2 with the addition of another waste processor, but also adds an additional source of fuel to the plant which addresses DG3.

Table 39 shows the results of the ENA for the Chinese steel manufacturing networks. The baseline scenario is a well-connected and well cycled network compared with other UIEs and industrial networks. There is not a huge reliance on single sources of flows, and the Robustness is towards the peak of the curve. The co-location scenario improves some of these metrics slightly such as MPL and AMI. The cycling decreases slightly in this network, and most other values remain consistent. The addition of the wetlands and pyrolysis actors has a much greater effect on the ecological performance. This network has a much greater value for MPL, AMI, and Cyclicity. As this network is modified, the flows become more constrained, and move more towards efficiency, away from redundancy on the Robustness curve. Both ASC and DC increase showing that greater constraint, but also a greater potential for this network to develop. The values for Single Source and Specialized Predator Fraction increases from the baseline, but this is due to the addition of the new actors that are specialized predators. Even though these additions increase the number of actors relying on single sources, the other benefits they created by being brough into the network counteract this to create a better performing network overall.

Table 39 Ecological metrics for baseline and modified Chinese steel manufacturing networks

Ecological Metric	Baseline	Co-Location	Wetlands and Pyrolysis
Cyclicity	2.155	2.111	2.490
Linkage Density	1.700	1.900	2.500
Prey Predator Ratio	1.000	0.722	0.750
Generalization	2.615	2.111	2.500
Vulnerability	2.615	2.923	3.333
Actors	20	20	20
Links	34	38	50
Connectance	0.085	0.095	0.125
Percentage of Connecting Actors	0.600	0.600	0.700
Specialized Predator Fraction	0.308	0.500	0.450
Finn Cycling Index	0.016	0.014	0.014
Mean Path Length	2.065	2.162	2.515
Average Mutual Information	1.461	1.668	1.828
Ascendency	30.473	35.985	36.697
Developmental Capacity	92.578	99.623	97.836
ASC/DC	0.329	0.361	0.375
Robustness	0.528	0.531	0.531
Shannon Index	4.439	4.618	4.874
Single Source	0.077	0.333	0.350
Normalized StDev of AMI	0.059	0.052	0.046
SCC	1	1	1
Actors in SCC	13	13	15

In all scenarios, the on-site power plant is the most central actor. However, in the wetlands and pyrolysis scenario, the wetlands are the second most central. The addition of this actor plays a huge role in the addition of cycling within the network and helps to increase the number of connections by almost 50%. In addition, the amount of grid electricity needed is reduced due to the pyrolysis reducing emissions and saving money.

7.4 City of Fayetteville

The final case study examined is around the city of Fayetteville, AR. The city has a population around 85,000 (US Census Bureau 2018) and is home to the main campus of the University of Arkansas with an enrollment of around 23,000 (University of Arkansas 2018). In addition, it has a number of industries located there including a major poultry processing plant. This provides a good test bed for an UIE. For this system, the water, energy, and nutrient networks are explored. Additionally, an embodied energy network is created to combine the energy and nutrient network. With this embodied network, modifications are made similar to the previous case studies.

In the network construction, it was important to identify the key actors of the city. These actors are the ones that, if altered, could have an impact on the performance of the systems of interest, and therefore are places where major consumption or transformation of water, energy, or nutrients occurs. The following actors were identified for this city: water supply, power plants (3), residential, commercial, industrial, wastewater treatment, biosolid management, agriculture, and the University of Arkansas. For each network, there are a number of assumptions that must be made to obtain the flow values. Values are calculated and/or estimated per year. In addition, values are normally rounded to a few significant digits. As is expected with networks of this scale, it is impossible to obtain precise and accurate data down to the gallon or kilowatt level.

7.4.1 Water

The water network for Fayetteville is of standard construction and is shown in Figure 29. There is a single main water source that provides water to the area, with two wastewater treatment plants for sewage. This main water source is Beaver Lake, and the Beaver Water District is the water service provided. They supply water to over 330,000 customers in Northwest Arkansas including the city of Fayetteville (Beaver Water District 2020). The city water system provides water to over 75,000 people in the area (City of Fayetteville 2020c). There are two wastewater treatment plants, in addition to a biosolids management site and a wet prairie sanctuary that are operated by the city (City of Fayetteville 2020b). The power plants in the area have their own water sources nearby, and therefore do not draw from Beaver Lake. As a result, they act independently from the main water system, but still draw a significant amount of water.

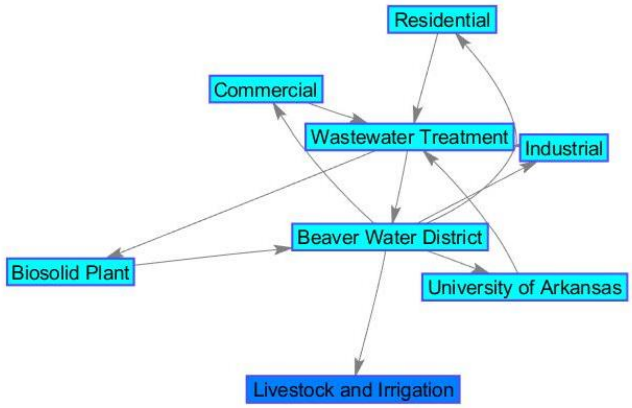


Figure 29 Network configuration for baseline Fayetteville water network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

For the baseline system, the water consumption needed to be obtained for each of the actors. As stated previously, all values are calculated/estimated on an annual basis and are rounded to the nearest million gallons. While the Beaver Water District provides water for more than just Fayetteville, only the water that is used within the city is accounted in this analysis. The residential water consumption was calculated using the average residential per capita water usage for the state of Arkansas (Dieter et al. 2018) and multiplying by the population of Fayetteville which resulted in a value of 2,770 million gallons per year. The industrial, commercial, and livestock and irrigation consumption numbers were estimated using values for Washington county (the county in which Fayetteville is located) and adjusting for the population of Fayetteville (Pugh and Holland 2015). The industrial consumption was estimated at 1,666 million gallons per year, the commercial consumption was estimated at 1,440 million gallons per year, and the livestock and irrigation consumption was estimated at 294 million gallons per year. The University of Arkansas water consumption was taken to be 230 million gallons per year (University of Arkansas Office of Sustainability 2013b). The natural gas power plant is air cooled and therefore does not have any water consumption. The coal power plant uses 3,536 million gallons per year (US Energy Information Administration 2018). The hydropower dam consumes 10,814 million gallons per year (Lampert et al. 2017). All of these values are summarized in Table 40.

Table 40 Water consumption values (annual million gallons) for different actors in the City of Fayetteville

Actor	Consumption
Residential	2,770
Industrial	1,666
Commercial	1,440
Livestock and Irrigation	294
University of Arkansas	230
Coal Power Plant	3,536
Hydropower Dam	10,814

For the water distribution system, it was assumed that there is a 16% loss through leaks in pipes, pumps, and other water infrastructure (US Environmental Protection Agency 2013). This is factored into the network by increasing the amount of water sent to each actor from the main water supply, with 16% of that water being a dissipation loss that is not recoverable. The remaining water is all assumed to be sent to the wastewater treatment facilities. Some of this water (25%) is then sent to the biosolid plant for further treatment. All water sent through the wastewater treatment or biosolid plant is assumed to be returned back to the main water supply. This network is not modified, but provides a baseline network for comparison.

Table 41 shows the ecological metrics for all of the baseline networks. For the water network, there is a Cyclicity value of 1.835 and FCI value of 0.283. While a good amount of the water is recycled (similar to that of ecological networks), the number of actors visited by that material is drastically lower as shown by the MPL value of 1.960. The Prey Predator Ratio is 0.875 meaning there is a good balance between which actors are consuming and which actors are being consumed. There is a large reliance on the central water source, showing a Specialized Predator Fraction of 0.750. The water network is the best performing ecologically of the baseline systems, which is to be expected given the prominence of water cycling and ubiquitous nature of water.

Table 41 Ecological metrics for baseline water, energy, and nutrients networks for City of Fayetteville

Ecological Metric	**Network**		
	Water	*Energy*	*Nutrient*
Cyclicity	1.835	0	0
Linkage Density	1.091	0.727	0.818
Prey Predator Ratio	0.875	0.125	1.200
Actors	11	11	11
Links	12	8	9
Connectance	0.099	0.066	0.074
Specialized Predator Fraction	0.750	1.000	0.600
Finn Cycling Index	0.283	0	0
Mean Path Length	1.960	1.135	2.226
Average Mutual Information	1.956	0.945	1.660
Alpha	0.525	0.274	0.441
Robustness	0.488	0.512	0.521

7.4.2 Energy

Similar to the water network, the energy network (shown in Figure 30) is a centralized system. There are three main power plants near Fayetteville, all operated by Southwestern Electric Power Company. These plants are the Beaver Lake Hydropower Dam, Flint Creek Coal Power Plant, and Harry D. Mattison Natural Gas Power Plant with nameplate capacities of 112, 558, and 349 MW respectively (US Energy Information Administration 2020). It is assumed that all electricity for the city comes from these three plants. The total electricity usage for Fayetteville in 2016 was 1,132,000 MWh (City of Fayetteville 2018). This must be further broken down to the individual actors to create the network. Using data for the state of Arkansas (US Energy Information Administration

2019), it was calculated that 38.5% of this is residential, 35.2% of this is industrial, and 26.3% of this is commercial. Additionally, the city used 18,552 MWh to treat and convey wastewater (City of Fayetteville 2018).

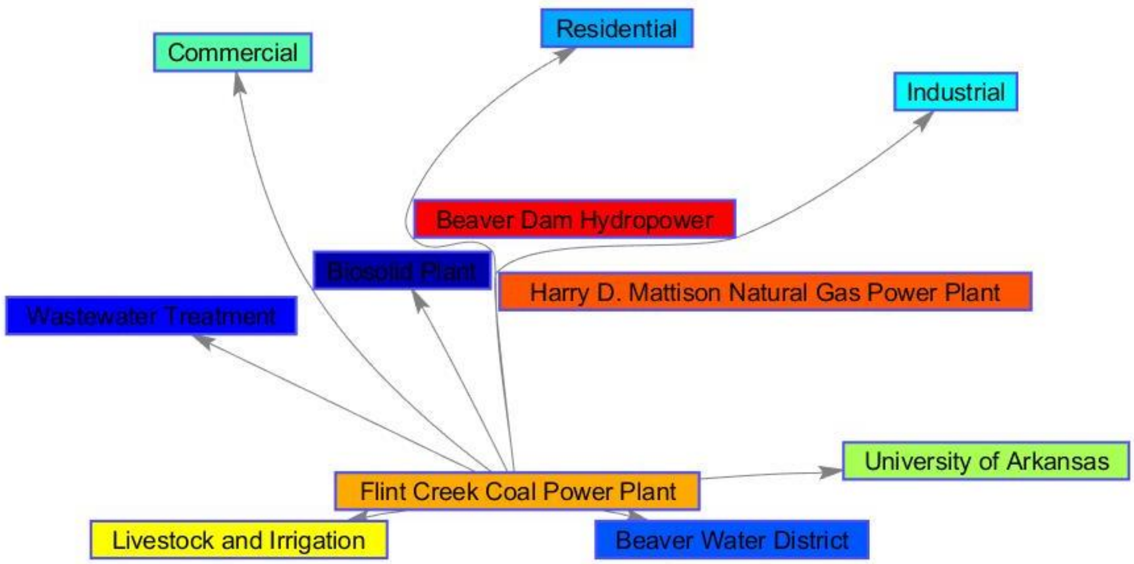


Figure 30 Network configuration for baseline Fayetteville energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Energy consumption for the University of Arkansas is estimated to be 120,000 MWh annually (University of Arkansas Office of Sustainability 2013a). It is assumed 15% of industrial energy use is consumed by agriculture accounting for the energy use in the livestock and irrigation actor. As with the water network, 25% of the energy use for wastewater treatment is assumed to be for the biosolids facility. All energy used is assumed to be dissipated, while any additional energy generated by the power plants is assumed to be exported from the system. Since it is impossible to know which power plant the city is drawing from at any given time, there are a few scenarios considered with different energy mixes:

- The baseline network relies solely on coal to provide energy. The coal power plant is the largest and the only one capable of providing all energy needed for the city.
- The second scenario (Figure 31) is a mix of the three power plants. It assumes that all of the generation at the natural gas and hydro plants are used for the city, with the remaining demand being met by the coal power plant.
- The final two scenarios introduce a new power supply that could be theoretically created around the biosolids plant. It is assumed that the plant would process biosolid waste to generate biogas that would be burned and generate electricity for the city. The first scenario (Figure 32) would place this biogas energy within the coal only network, while the second (Figure 33) would place it in the mixed energy use. In all cases, it is assumed the biogas plant supplies 10% of the needed energy for the system.

These different scenarios examine the effect of having a single source vs. multiple sources of energy (DG3). Additionally, by including the full network with the specific power plants, this allows for those multiple sources to be explored beyond a generic power plant actor (DG1).

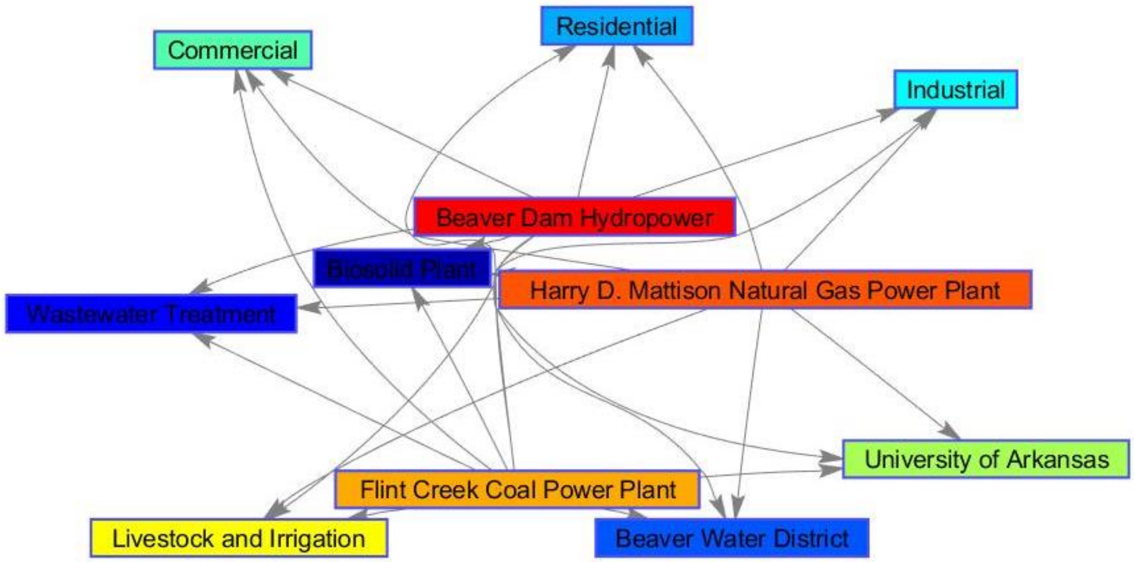


Figure 31 Network configuration for mixed Fayetteville energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

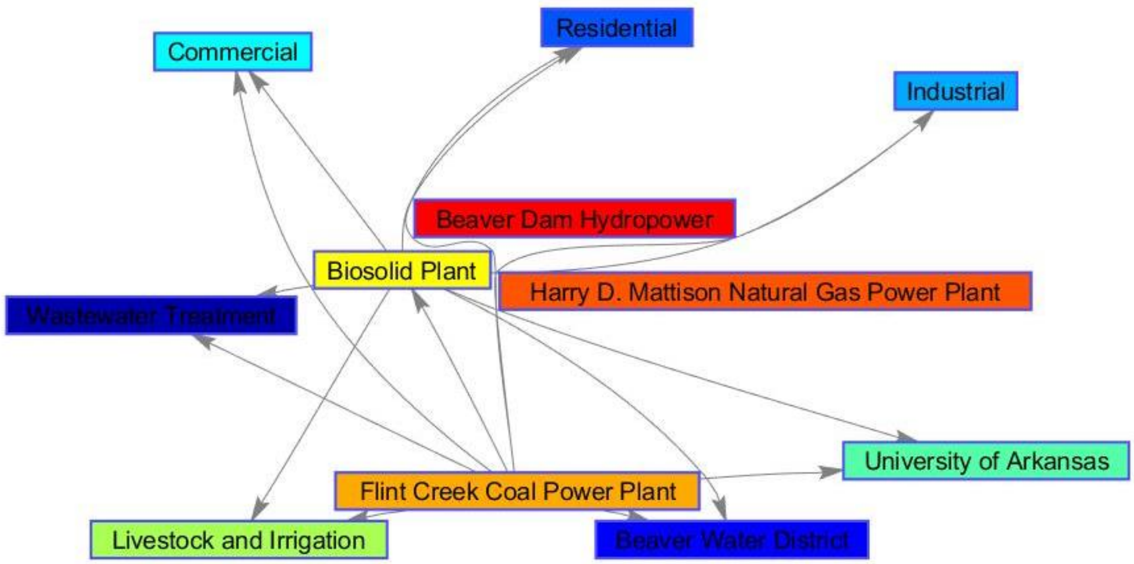


Figure 32 Network configuration for biosolid Fayetteville energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

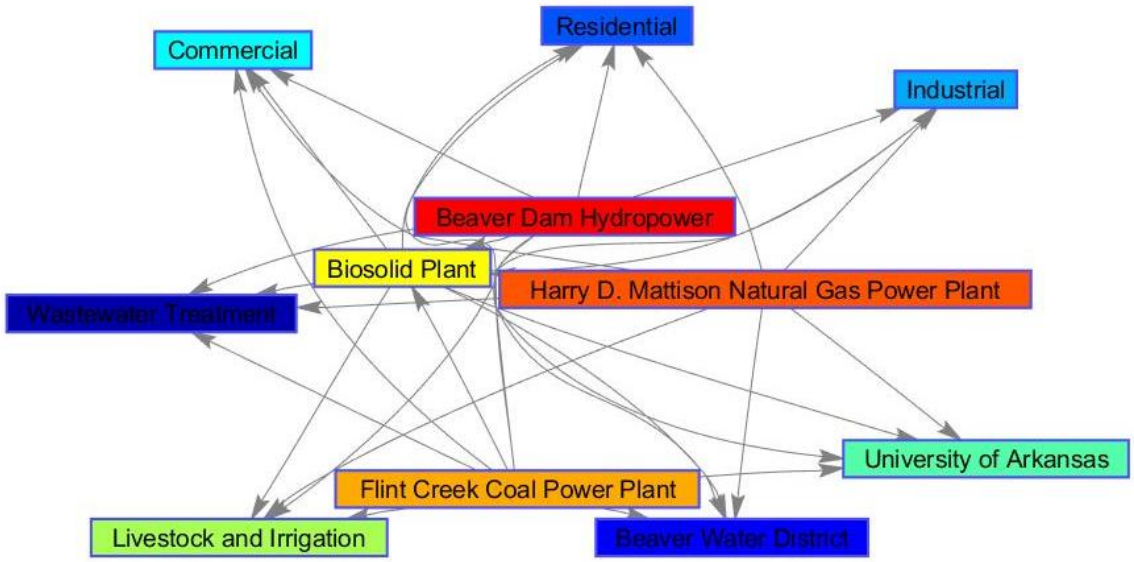


Figure 33 Network configuration for biosolid and mixed Fayetteville energy network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

As shown in Table 41, in the baseline energy network there is no cycling, which is expected as energy is not easily cycled. Additionally, the results show a much larger number of predators than prey, with 8 predators but only 1 prey. With only one source of electricity, this leaves the city very vulnerable. MPL has a value of 1.135 meaning that most of the flow visits only a single actor before it leaves the network. The energy network has the lowest performance of the three baseline networks. The results for the modified energy networks are shown in Table 42. The flow metrics remain fairly consistent across all scenarios, but the structural metrics increase considerably. While there is no change in the lack of cycling, the number of links doubles or triples in the new scenarios. Additionally, the Specialized Predator Fraction decreases to 0 in the cases when there is a mix of coal, natural gas, and hydropower. These modified networks should be much more resilient than the single source network considered to be the baseline. These networks will be explored further in the embodied energy section that follows.

Table 42 Ecological metrics for modified Fayetteville energy networks

Ecological Metric	Network		
	Mixed	*Biogas*	*Mixed + Biogas*
Cyclicity	0	0	0
Linkage Density	2.182	1.364	2.818
Prey Predator Ratio	0.375	0.250	0.500
Actors	11	11	11
Links	24	15	31
Connectance	0.198	0.124	0.256
Specialized Predator Fraction	0	0.125	0
Finn Cycling Index	0	0	0
Mean Path Length	1.144	1.135	1.144
Average Mutual Information	0.929	0.947	0.934
Alpha	0.268	0.266	0.263
Robustness	0.509	0.508	0.507

An additional analysis was conducted on the emissions related to each energy source, with Table 43 showing these results. All scenarios have a reduction in emissions when compared with the baseline coal network. The biogas production by itself reduces the emissions by almost 10%, and in combination with the natural gas and hydropower plants can reduce emissions by almost 25%.

Table 43 Total Emissions and Percent Reduction for Different Scenarios in Fayetteville Energy Network

Scenario	Emissions (tons CO2E)	Percent Reduction
Baseline (Coal)	1,534,195	-
Split	1,289,579	15.9%
Biogas	1,387,139	9.6%
Split + Biogas	1,174,523	23.4%

7.4.3 *Nutrients*

The nutrient network (shown in Figure 34) is focused on nitrogen, specifically the nitrogen in food and wastewater. Information about food consumption rates, nitrogen content of food, fertilizer rates, amount of food waste, percentage of eating out, and the composition of nitrogen in wastewater that is required to construct this network was taken from the extensive analysis of (Cohen 2018). Additional data was gathered on solid waste, both the amounts and nitrogen content of this waste. The city of Fayetteville produces 1,708 pounds of solid waste per capita per year, with 19% of this waste being diverted from landfills (City of Fayetteville 2020a). 18% and 17% of all food consumed is discarded as waste by the residential and commercial sector, respectively (Mitchell 2015b). The University of Arkansas is estimated to produce 460 metric tons of food waste annually (Mitchell 2015a). It is estimated that there is 3% nitrogen in food waste across all sectors (Esteves and Devlin 2010).

The baseline network assumes no food consumed locally is grown within the network. Therefore, all food is imported into the system. Nitrogen is imported to the commercial actor to be distributed to the residential actor through either restaurants or grocery stores. The industrial actor does not interact with either the commercial or residential actor. All waste nitrogen is either dissipated (non-recoverable), exported (recoverable), or sent to the wastewater treatment or biosolids facility. A small percentage of wastewater nitrogen (4%) is sent to and livestock and irrigation actor and it is assumed that 25% of the nitrogen from the biosolid facility has the same fate.

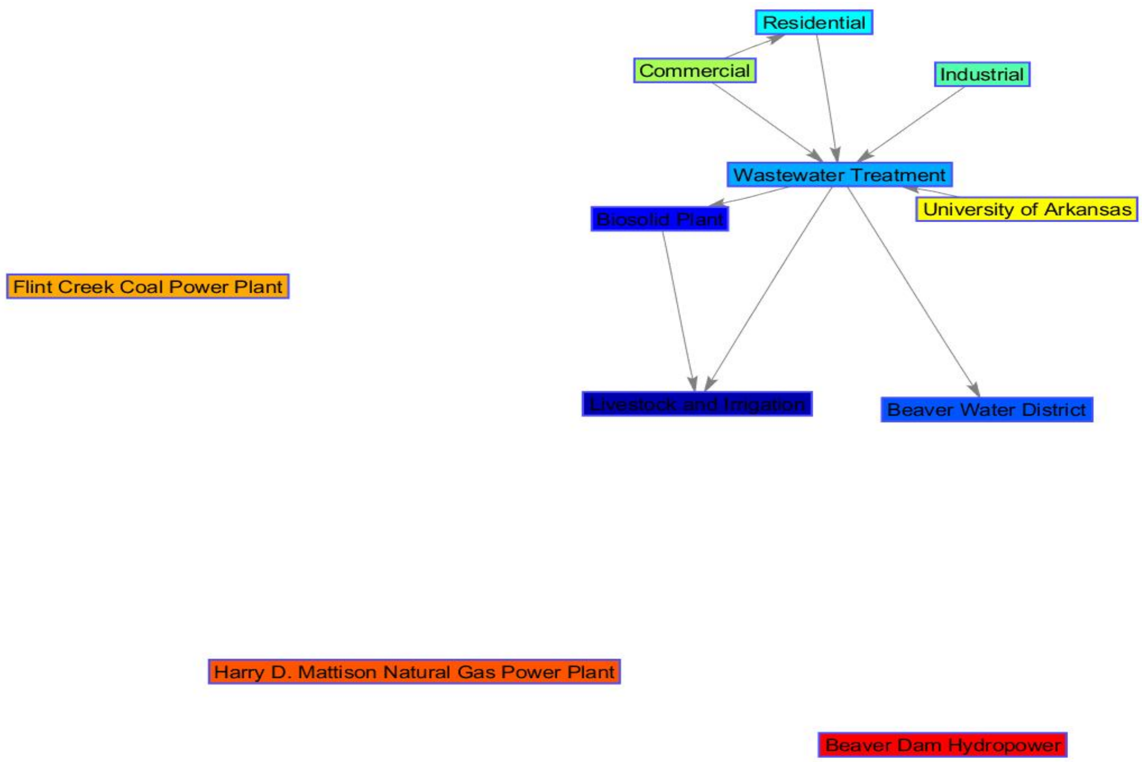


Figure 34 Network configuration for baseline Fayetteville nutrient network. Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

The ecological performance of the baseline nutrient network (Table 41) falls somewhere between the water and energy networks. There is no cycling present as shown by the Cyclicity and FCI values. The Prey Predator Ratio is 1.200 showing a fair balance between consumers and consumed. Also, the MPL value of 2.226 shows a higher number of actors are visited by flow than both the water and energy networks. This network has the lowest Specialized Predator Fraction, but still more than 50% rely on single source. This baseline network could be modified to improve cycling (DG2) and an increase in the number of sources for food (DG3). One suggested modification as shown in the energy network is the addition of a biogas plant to process biosolid waste and generate usable energy. However, when only the nitrogen flows are considered, this does not actually result in any increased cycling or additional source. For this reason, in addition to the normal nutrient network, an embodied energy network based around nutrients was created. This allows for the biogas production to be included in this network by putting everything into a common currency. This also allows for this network to be combined with the energy network to create a larger networking representing more interactions. Additional information about the energy content of food and waste was required to create this network. The percentage of nitrogen in human waste was used to determine the total amount of human waste generated in the network (University of Kentucky 2018). The average energy required to produce food was estimated to be 113 kWh/kg (Alexandrou, Tenbergen, and Adhikari 2013). Finally, estimates were made to calculate the amount of potential energy generated from the biogas plant using information about the percentage of volatile solids in human waste, the thermal content of biogas, conversion efficiency, and biogas density (Schuster-Wallace, Wild, and Metcalfe 2015). In addition to the biogas production modification, this network also adds a modified scenario in which 20% of the food is grown inside of the network as opposed to all of it being imported. There is one final scenario in which both the biogas generation occurs, and this food is grown within the network. This has the benefit of adding another source of flow, decreasing the amount of needed imports, and increasing the amount of cycling that occurs. The results of these modifications are shown in Table 45.

7.4.4 *Embodied Energy*

As mentioned, the embodied energy network combines the nutrient and energy networks. This allows a more complete picture of the interactions and flows that occur because it examines more than a single flow type. In this network, a connection may represent multiple material flows that are additive. It is important to note that a modification to the nutrients in the network may not have any effect on the energy of the network, even though the results change for this combined network. The baseline network (shown in Figure 35) for the embodied energy system is the combination of the baseline nutrient network and the baseline energy network (sole energy source of coal). The modified networks are those previously mentioned for the nutrient and energy networks in different combinations. This results in 8 different scenarios that were analyzed. The network incorporating all modifications is shown in Figure 35. These different scenarios are outlined in Table 44 with the ecological results being presented in Table 45. When a food source is added to the network, this results in cycling occurring. The same is true for the biogas production. However, the amount of cycling is still extremely low with the FCI reaching a maximum of 0.002. Although cycling occurs, the majority of the energy in the network passes through linearly. As a result, the other flow metrics show very little change.

There are slight increases in MPL and AMI seen as the network is further modified, while Robustness and ASC/DC fluctuate up and down through the modification scenarios. Due to the constraints of the network, the amount of imported embodied energy is only reduced by 3%.

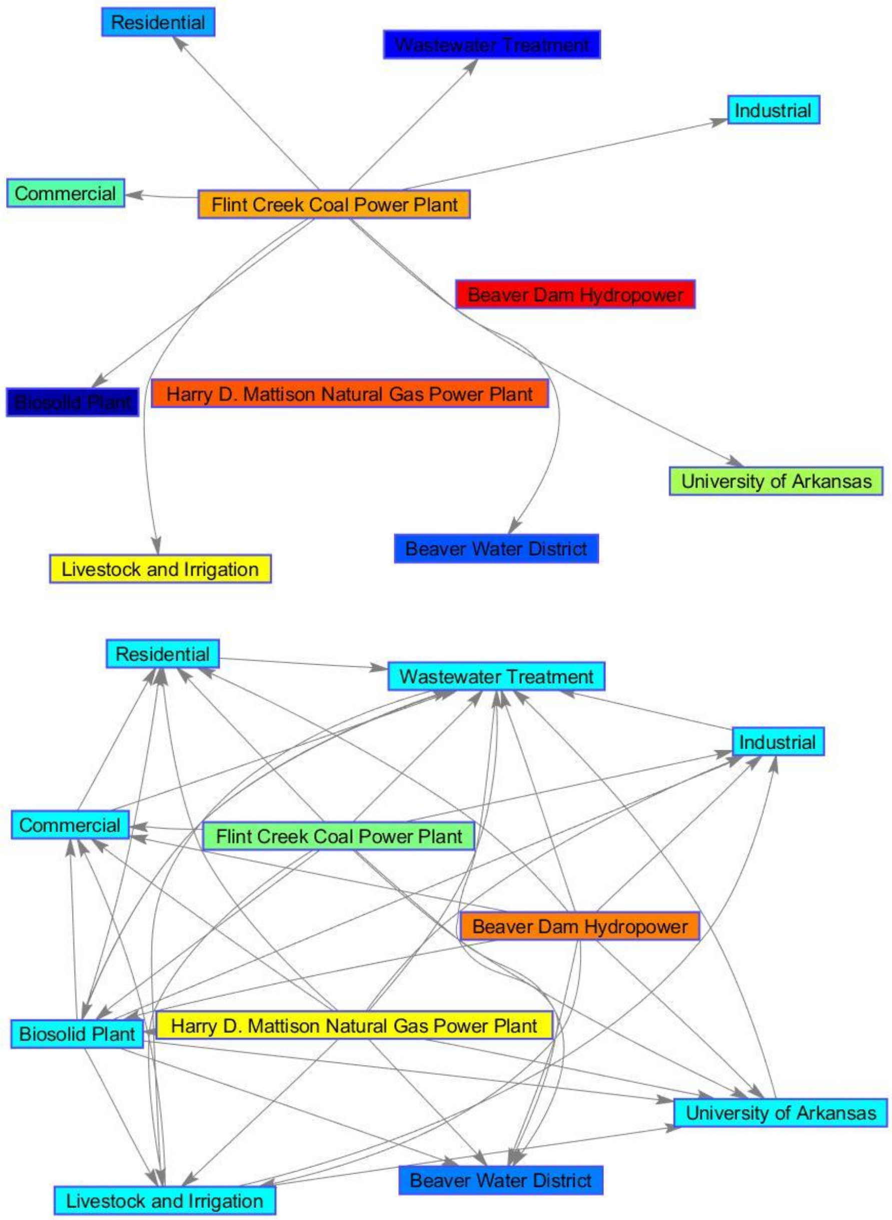


Figure 35 Network configuration for Fayetteville embodied energy networks, baseline (top) and fully modified (bottom). Actors of the same color are in one Strongly Connected Component, while actors that are their own color are not in a Strongly Connected Component

Table 44 Embodied energy network scenarios for Fayetteville embodied energy network. Split energy source refers to combination of coal, natural gas, and hydropower.

Scenario	Energy Source	Food Source in Network?	Biogas Production?
1	Coal	No	No
2	Coal	Yes	No
3	Coal	No	Yes
4	Coal	Yes	Yes
5	Split	No	No
6	Split	Yes	No
7	Split	No	Yes
8	Split	Yes	Yes

Table 45 Embodied energy scenario results for City of Fayetteville

	Scenario							
Ecological Metric	*8*	*4*	*3*	*7*	*2*	*6*	*5*	*1*
Cyclicity	2.268	2.268	1.856	1.856	1.773	1.773	0	0
L_D	3.818	2.364	2.091	3.545	1.818	3.273	3.000	1.545
P_R	1.25	1.000	0.875	1.125	1.000	1.25	1.125	0.875
N	11	11	11	11	11	11	11	11
L	42	26	23	39	20	36	33	17
P_S	0	0	0	0	0	0	0	0.375
FCI	0.002	0.002	0.001	0.001	0	0	0	0
MPL	1.291	1.291	1.224	1.224	1.267	1.267	1.213	1.213
AMI	1.015	1.019	1.009	1.005	0.980	0.977	0.982	0.986
ASC/DC	0.248	0.249	0.251	0.250	0.237	0.236	0.246	0.247
R	0.499	0.500	0.501	0.500	0.492	0.491	0.498	0.498

7.4.5 Conclusions of Fayetteville Case Study

Through this case study, a fully networked city was explored through the lens of ecology and modified with the proposed design guidelines. One of the biggest vulnerabilities of this system are the single sources for critical resources (food, water, and energy). The modified networks showed how the resilience (i.e. robustness and redundancy) of these systems could be increased through adding additional sources of those resources. The structural metrics are most affects by these changes with significate increases in Cyclicity being seen. The additional links also lead to fewer actors being a specialized predator and the demand on any one single source is decreased as a result. Similar to the automotive case study, the relative amounts of the flows that are modified are low and therefore the resulting impact on the flow-based metrics is minimal. Although structural cycling is increased, the amount cycled is so low that it is almost negligible. AMI does increase some as the network is further modified, meaning there is greater constraint on the flows. Beyond the ecological metrics, the reduction in emissions due to a change in energy mix is non negligible. Additionally, there is a decrease in the amount of imported embodied energy. This shows the strength of the design guidelines beyond simply raising ecological performance to other traditional sustainability goals.

7.5 Conclusions

In this chapter, it is shown how the design guidelines from Chapter 6 can be applied to various networks. Through these case studies, it is clear that the design guidelines are effective at both increasing ecological performance and creating more sustainable systems defined by reduced emissions and greater resource utilization. Specifically, cycling was increased in every case study. Many of the new actors introduced act in the decomposer role that has been identified as critical to the function of natural ecosystems. Other critical actors included the centralized infrastructure (power plants, water distribution, etc.) and the urban centers that consume many of the resources and generate waste. Even with these improvements, these human-designed systems still have a significant way to go in order to achieve similar performance to that of the median natural systems. Still, the modifications to these systems allow for them to move more towards that natural ecological performance and adopt some of the fundamental characteristics that sustain them.

In all scenarios, the structural metrics showed much greater improvement than the flow-based metrics. This raises the question of the utility of structural only modeling if the change in metrics is dramatically different. Structural modeling is beneficial for initial analysis to rapidly assess the characteristics of a system, especially cycling and the reliance on single sources. It has a low data requirement, meaning potential modification scenarios can be tested very quickly. However, as shown here, improvement in structural metrics does not always correlate to improvements in the flow-based metrics. This means structural modeling is an incomplete analysis. Therefore, design decisions should not be made based on structural modeling alone. It should only be used in the initial analysis phase when exploring as shown in Automotive Manufacturing case study here.

CHAPTER 8. SUMMARY AND FUTURE WORK

8.1 Summary

Through this work, there are four fundamental contributions that are highlighted here.

1. **The addition of new ecological metrics for use in urban and industrial networks.** The additional metrics included in this dissertation allow for the identification of key actors, which has previously not been done. Not only is this beneficial for the urban-industrial networks, but it also beneficial for ecological networks in greater identifying the key species and how they interact with all other species in an ecosystem. The analysis shows there is no clear functional role that is most central to the human-designed systems. However, it did highlight how many of these systems heavily rely on centralized infrastructure and the potential vulnerability that creates.
2. **An ecologically analyzed dataset of urban-industrial systems.** A dataset of this kind has never been complied and analyzed before. Previously, the only compiled dataset consisted of networks with structural connections and did not include the flow values. Additionally, individual networks have been analyzed with flow, but have never been complied for comparative analysis. This dataset allows for a more general and broad understanding of the typical function and performance of human-designed systems by calculating average and median values. The inclusion of only

flow-based networks provides roughly double the number of metrics that are used for analysis giving a far greater number of data points from which to draw conclusions about core characteristics.

3. **Further testing and validation of the application of ecological metrics to human-designed systems.** The use of ENA for analysis in non-ecological systems is in its infancy but continuing to grow. This novel field has the potential to completely change how analysis and design of all systems is performed. By using this tool on a greater number of networks, it shows the flexibility of this analysis while providing more examples of how it can be used. The results of this dissertation validate past research on the performance of human-designed networks compared with their ecological counterparts. While ENA is not a perfect tool, it is proven once again to be useful in understanding these systems and identifying the potential to increase the sustainability.
4. **The creation and testing of ecologically derived design guidelines for sustainable Urban-Industrial Ecosystems.** These design guidelines propose a way to create sustainable systems that better utilize energy and materials while increasing resilience. This furthers what has previously only been used for analysis into design with quantified motivation and results. Through the testing, it is shown that these guidelines increase the ecological metrics while also meeting traditional sustainability design goals of reduced emissions and consumption.

By examining the literature, critical gaps were identified in the current understanding and modeling of urban and industrial systems. Urban Metabolism and Material Flow Analysis offer accounting methods for the flows of these networks, but do not offer much in the way of actual analysis or direction on how to make improvements. The suggestions for increased sustainability are unguided and without clear numerical analysis that can validate those suggested changes. In addition, these systems are often modeled too simply, not taking into account some of the critical infrastructure that allows them to function. Therefore, both a better analysis tool and design methodology are needed to create the sustainable systems that are required for the future. Ecology offers a useful pursuit for sustainable design through the structures found in natural ecosystems. These systems are wholly independent of centralized infrastructure and only consume what can be found within the system boundaries. They are adaptable to perturbations such as natural disasters and have many mechanisms to recycle critical nutrients. They are, by definition, sustainable as they have survived the entire existence of life on this planet. Thus, they are the perfect inspiration for these human-designed systems as they strive for sustainability. Bio-inspired design is not novel in these systems but has scarcely been used at the network level to fundamentally shift the design of cities and industry. Additionally, with Ecological Network Analysis, ecologists have created a useful tool in understanding the characteristics of these systems. Ecological Network Analysis is helpful in addressing the gaps of previous modeling by providing numerical analysis for comparison between systems. By comparing to natural ecosystems, one can quantify the gap in performance between natural and human-made systems. Therefore, ecology is able to provide perhaps the most sustainable systems from which to draw inspiration from while also providing a form of analysis to better quantify these systems and the sustainability they look to achieve.

It is imperative to remember that the analogy between natural and human systems is far from perfect. These systems are fundamentally different in their goals, drivers, and limitations. Natural systems simply look to survive while human systems are driven primarily by economics. The simple existence of currency in human systems changes how they operate as flows may exist that would never make sense in a predator-prey driven network. Natural systems are much more limited in resources, only able to access what is within a local area. On the other hand, human systems are global and digital, with more goods than not being imported from outside the system boundaries. These differences can help to explain a lot of the gap between the systems.

The Urban-Industrial Ecosystems analyzed here are wide ranging and therefore provide an excellent dataset for understanding human-designed systems. This dataset provides a much deeper analysis due to the inclusion of only flow-based networks, furthering the work done to previously analyze the structure of Eco-Industrial Parks. This is the first dataset of its kind to be analyzed using these metrics. The results show a similar level of performance across all human-designed systems. They mostly fall within a range that is below even the median value for the natural systems. The human-designed systems have lower cycling, resource utilization, and either have a greater focus on redundancy or efficiency. The natural systems balance these traits while recycling substantially more resources. This confirms previous work, but with a greater number of metrics and a more diverse set of systems. Through that diverse set of systems, it was also possible to analyze them based on network type and the inclusion of specific actor types. The results show how certain actors can impact the performance of these systems. The natural environment, industry, and agriculture all play a vital role in human-designed systems through their functions of processing raw material and waste and acting to connect these systems, thus they improve the performance when they are present. Meanwhile, the utility actors have a negative effect on performance due to the sole reliance on these for resources. Given the effect of specific actors on network performance, it was important to identify the key actors within these systems. This was done by expanding the analysis beyond the single value metrics to include those that took all network interactions into account.

That expansion led to the inclusion of Centrality, Utility, Mixed Trophic Impact, Control, and Dependence. These metrics allowed for those key network components to be identified. Through the analysis with these metrics, it further highlighted the difference between these systems. The natural systems consistently had decomposers identified as the most important actor, while the human-designed systems lacked any consistency in that key role. The key actors in the UIEs and EIPs were most often central infrastructure such as power plants or water distribution systems. There is great vulnerability in these systems that rely so heavily on those central distributors to supply resources throughout the system as shown by the lesser performance of UIEs with those utility actors present. Some of the other key actors included those that took in waste as they were connected to the majority of other actors. However, these actors seldom process this waste to create anything useful for the system like the decomposers of the natural systems. Thus, this analysis revealed the two areas that have the most potential for sustainable change in human-designed systems: the centralized infrastructure that provides resources (analogous to primary producers) and the waste processors (analogous to decomposers). This observation directly influenced the design guideline creation. Of particular note in this analysis were the Mutualism Index values. In previous literature, it was generally thought that this value should be above 1 as to maximize the number of mutualistic relationships present in the system. This was, on average, true for the human-designed systems. However, the average for the natural systems analyzed was below 1. This indicates that perhaps these systems operate best when there is more competition.

The correlations between ENA metrics presented surprisingly poor results. Overall, there is little correlation between these single value metrics, making it difficult to predict ecological performance. The metrics with the strongest correlations are Links and Linkage Density. This indicates that one of the best indicators of ecological performance is simply a greater number of connections. However, those metrics seem to only correlate with greater performance in the other structural metrics. This trend is similar across all of the metrics with the structural metrics having stronger correlations with other structural metrics than with the flow-based ones. The same is true with the flow-based metrics that have stronger correlations with other flow-based metrics. This means there is not a single metric to design around when looking to create better performing networks. An increase in the number of connections can be beneficial, but if the flow values of those links are not substantial, it will have little effect on the overall system performance. The importance of this was shown in many of the case studies where additional links were added, but the amount of those flows was relatively small and thus there was little change in the ENA metrics. Therefore, the focus on the design principles for UIEs was not centered around one single metric, but rather on the combined quantitative and qualitative observations of the analysis. This led to the creation of three design guidelines which are as follows. DG1: Include all baseline actors for a specific network type to properly model and show performance. DG2: Implement waste recovery and recycling actors to increase cycling performance and resource utilization. DG3: Introduce additional sources of resources to create more resilient systems. These design principles were created with the goal of increasing the ecological performance of these systems, while also increasing sustainability as defined by reduced resource consumption and increased resilience.

The testing of the design guidelines was performed by modifying various human-designed systems. The modified networks included some of the UIE dataset, as well was newly generated networks designed specifically for this testing. These modifications were directly related to one or more of the guidelines proposed. These modifications rely on fully understanding the networks they function within as well as identifying where there is potential to create new roles. These new roles include processing waste, providing additional sources of resources, and utilizing resources that would otherwise be exported from the system. Overall, the ecological performance of these systems was increased, especially for the structural metrics. By including more cycling and sources, the gap in ecological performance was lessened. Additionally, these systems saw a decrease in emissions of importing of external flow. Thus, the design guidelines were able to accomplish the goal set forth. However, the improvement in these systems was less than expected. This was due to the magnitudes of the flows being altered. The relative size of many of these flows was small, leading to minimal impact on ecological performance. For human-designed systems, more connections are good, but more impact will come from meaningful connections that are made. To further this, not only meaningful connections need to be made, but meaningful connections that have the relative size to impact the greater system.

8.2 Future Work

Expansion of dataset

In this dissertation, 77 human-designed systems are analyzed. The majority of these only include structural information and are centered around industry. ENA is not limited to these types of networks, and as such could be applied to any system. This could include digital infrastructure, factory operations, or geospatial networks. The greater number of these systems that are analyzed, the greater knowledge there will be about not just these systems but systems in general. The network type analysis shown in Chapter 4 could be conducted on a much larger scale to include all of these different flow types. This would allow for these systems to be more specifically sorted instead of lumped together. This has the potential to highlight vulnerabilities in security networks or generate a new design structure for assembly lines. The inspiration from nature is endless, and the more this dataset grows, the further that inspiration can be taken.

Further testing of design guidelines and creation of new guidelines

The guidelines proposed here were created only using the networks shown. While this is a robust dataset, it does not encompass every type of network or all of the possibilities within those networks. These guidelines need to be tested further to prove their effectiveness. The ecological performance is shown for all case studies, but traditional sustainability metrics are only shown for a few, which just scratches the surface. These more traditional metrics of decreased waste and emissions need to be validated alongside the ecological ones. Economic feasibility is also crucial for real-world adoption of these guidelines. This analysis shows what would be theoretically possible, but much greater analysis is needed to understand the viable designs for these systems. This could be done through correlating the ecological and sustainability metrics similar to what has been shown by Layton (Layton et al. 2016a). Ultimately, this could lead to optimization of these metrics that maximize those sustainability metrics. Beyond the further testing, the guidelines can be modified, improved, or even new guidelines created. These guidelines could be specific to certain network types as what may improve a nitrogen network may actually harm a water network. Human-designed systems are much more varied than natural ecosystems and each one has specific requirements that must be met.

Integrated design tool

One suggestion to further the use of ecology in design is through an integrated design tool. This tool would be capable of rapidly generate network configurations and modifying flows that are optimized for ecological performance. Cost and emissions could also be integrated into this tool to allow for a full suite of analysis. The tool would take in the basic system information, allowing a network to be created around the basic structures known within the system (e.g. power plant, hospital, school, etc.). It could use the design guidelines proposed here to make modifications and improvements or be optimized to whatever criteria is most desired. The simplicity of modeling these systems as a matrix of flows allows for such a tool to easily identify performance gaps and potential for improvement.

8.3 In Closing

Urban and industrial systems are some of the most important human-designed systems that have an incredible impact on critical resources such as water, energy, and food. These systems must be continually improved and made more sustainable in order to survive. Specifically, the resilience of these systems can be further improved. With every new model, new insight is gained about these systems from how they operate to how they are affected by disruption. This dissertation adds to that insight by modeling and understanding these systems through the lens of ecology. It is one of the first steps towards creating biologically inspired human-designed that start to capture some of the potential of nature. The Urban-Industrial Ecosystems here are simplistic models of extremely complex systems, but they allow one to understand some of the core characteristics present. While these systems may never achieve the same level of sustainability, there is huge potential to move in that direction and further reduce human impact.

APPENDIX. ENA RESULTS AND NETWORK CONFIGURATIONS FOR ALL SYSTEMS

This appendix includes the full ENA results for all of the systems analyzed in this dissertation. This includes all structural and flow-based metrics, as well as the additional metrics examined in Chapter 5 for the UIEs, EIPs, and Food Webs. Specifically, for the UIEs examined in Chapter 4, there is the flow matrix and network configuration diagram showing how it is connected. The colors in each of these indicates the actors that are a part of a Strongly Connected Component. As stated, for some networks there are multiple cases that may include different years, cities, or configurations. Where possible, the network configurations and results are condensed as to not repeat the same data twice. For the flow matrices, all flows are from the columns to the rows. The units are excluded, but all flows are on an annual basis and in a common currency. The original sources can be checked to find the units for these flows.

		0	1	2	3	4	5	6	7	8	9	10	Exports	Dissipation
	Imports	0	9	33.8	13.5	5.2	11.1	2.7	5.8	10.2	0	0	0	0
1	**Desert**	0	0	25.1	0	0	0	0	0	0	0	0	0	8.6
2	**Near-surface atmosphere**	0	16.7	0	2.3	0	0	0	0	3.2	0	0	0	46.9
3	**Crops**	0	0	11.6	0	9.1	2.1	0	0	0	11.6	0	1.7	0
4	**Dairies**	0	0	2.7	7.9	0	1.4	0	0	0	0	0	2.5	0
5	**Humans**	0	0	0	0	0	0	0	11.5	0	0	2.3	0	0
6	**Pets**	0	0	0	0	0	0	0	0	2.4	0	0	0	0
7	**Wastewater**	0	0	11.4	1.4	0	0	0	0	0	1.5	0	0.6	0
8	**Urban landscapes**	0	0	6.4	0	0	0	0	0	0	6.4	5	0	0
9	**Subsurface**	0	0	0	9.9	0	0	0	0	1.1	0	0	0	0
10	**Landfills and Palo Verde**	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 36 Flow matrix for Central Arizona-Phoenix Nitrogen network

		0	1	2	3	4	5	6	7	8	9	Exports	Dissipation
	Imports	0	9	33.8	13.5	5.2	11.1	2.7	5.8	10.2	0	0	0
1	**Desert**	0	0	25.1	0	0	0	0	0	0	0	0	8.6
2	**Near-surface atmosphere**	0	16.7	0	2.3	0	0	0	0	3.2	0	0	46.9
3	**Crops**	0	0	11.6	0	9.1	2.1	0	0	0	11.6	1.7	0
4	**Dairies**	0	0	2.7	7.9	0	1.4	0	0	0	0	2.5	0
5	**Humans**	0	0	0	0	0	0	0	11.5	0	0	2.3	0
6	**Pets**	0	0	0	0	0	0	0	0	2.4	0	0	0
7	**Wastewater**	0	0	11.4	1.4	0	0	0	0	0	1.5	0.6	0
8	**Urban landscapes**	0	0	6.4	0	0	0	0	0	0	6.4	5	0
9	**Subsurface**	0	0	0	9.9	0	0	0	0	1.1	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0

Figure 37 Flow matrix for Central Arizona-Phoenix Nitrogen network without Landfill actor

		0	1	2	3	4	5	6	Exports	Dissipation
	Imports	0	13.92	0	0	0	0	0	0	0
1	**Human Bodies**	0	0	1.45	4.18	1.7	2.08	0.05	3.5	0.96
2	**Landfill**	0	0	0	0	0	0	0	1.45	0
3	**Incineration**	0	0	0	0	0	0	0	4.18	0
4	**Sewage Effluent**	0	0	0	0	0	0	0	1.7	0
5	**Atmospheric Release**	0	0	0	0	0	0	0	2.08	0
6	**Circular Outputs**	0	0.05	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0

Figure 38 Flow matrix for 1990 Toronto Nitrogen network

		0	1	2	3	4	5	6	Exports	Dissipation
	Imports	0	16.64	0	0	0	0	0	0	0
1	**Human Bodies**	0	0	1.27	1.8	3.97	6.72	0.89	4.04	1.15
2	**Landfill**	0	0	0	0	0	0	0	1.27	0
3	**Incineration**	0	0	0	0	0	0	0	1.8	0
4	**Sewage Effluent**	0	0	0	0	0	0	0	3.97	0
5	**Atmospheric Release**	0	0	0	0	0	0	0	6.72	0
6	**Circular Outputs**	0	0.89	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0

Figure 39 Flow matrix for 2001 Toronto Nitrogen network

		0	1	2	3	4	5	6	Exports	Dissipation
	Imports	0	16.6	0	0	0	0	0	0	0
1	**Human Bodies**	0	0	2.32	0.35	3.39	7.03	0.4	4	1.15
2	**Landfill**	0	0	0	0	0	0	0	2.32	0
3	**Incineration**	0	0	0	0	0	0	0	0.35	0
4	**Sewage Effluent**	0	0	0	0	0	0	0	3.39	0
5	**Atmospheric Release**	0	0	0	0	0	0	0	7.03	0
6	**Circular Outputs**	0	0.4	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0

Figure 40 Flow matrix for 2004 Toronto Nitrogen network

		0	1	2	3	4	5	6	Exports	Dissipation
	Imports	0	360	11	50	0	0	0	0	0
1	**Forestry**	0	0	203	63	0	0	84	0	0
2	**Production and trade of timber products**	0	0	0	30	150	0	34	0	0
3	**Production and trade of paper products**	0	0	0	0	0	220	57	0	0
4	**Consumption of timber products**	0	0	0	0	0	0	100	0	0
5	**Consumption of paper products**	0	0	0	134	0	0	86	0	0
6	**Incineration and waste management**	0	0	0	0	0	0	0	0	361
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0

Figure 41 Flow matrix for baseline Swiss Lowlands Timber/Paper network

		0	1	2	3	4	5	6	Exports	Dissipation
	Imports	0	360	11	0	0	0	0	0	0
1	**Forestry**	0	0	203	63	0	0	84	0	0
2	**Production and trade of timber products**	0	0	0	30	150	0	34	0	0
3	**Production and trade of paper products**	0	0	0	0	0	440	37	0	0
4	**Consumption of timber products**	0	0	0	0	0	0	100	0	0
5	**Consumption of paper products**	0	0	0	384	0	0	56	0	0
6	**Incineration and waste management**	0	0	0	0	0	0	0	0	311
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0

Figure 42 Flow matrix for modified Swiss Lowlands Timber/Paper network with increased paper consumption

		0	1	2	3	4	5	6	Exports	Dissipation
	Imports	0	360	426	0	0	0	0	0	0
1	**Forestry**	0	0	203	63	0	0	84	0	0
2	**Production and trade of timber products**	0	0	0	102	510	0	117	0	0
3	**Production and trade of paper products**	0	0	0	0	0	220	57	22	0
4	**Consumption of timber products**	0	0	100	0	0	0	0	0	0
5	**Consumption of paper products**	0	0	0	134	0	0	86	0	0
6	**Incineration and waste management**	0	0	0	0	0	0	0	0	344
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0

Figure 43 Flow matrix for modified Swiss Lowlands Timber/Paper network with increased timber consumption

		0	1	2	3	4	5	6	Exports	Dissipation
	Imports	0	15.8	1.54	0	0	0	0	0	0
1	**Wastewater treatment plants**	0	0	0	1.37	0.8	0.12	1.45	12.06	0
2	**Septic tanks**	0	0	0	0	0	1.37	0	0	0
3	**Irrigated crops**	0	0	0	0	0	1.37	0	0	0
4	**Palo Verde Power Plant**	0	0	0	0	0	0	0	0	0
5	**Groundwater**	0	0	0	0	0	0	0	0	0
6	**Biosolids**	0	0	0	0	0	0.36	0	0	0
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0

Figure 44 Flow matrix for Central Arizona-Phoenix Wastewater Nitrogen network

		0	1	2	3	4	5	6	7	8	9	10	11	12	Exports	Dissipation
	Imports	0	3.7	17	6.2	0.09	1.1	0	7.8	3	0	0	0	0	0	0
1	**Food Processing**	0	0	0	0	0	2.82	0	0	0	0	0	0	0	0	0.98
2	**Livestock**	0	0	0	0	0	0.1	0	0	0	0	0	0	0	0	16.9
3	**Copra Production**	0	0	0	0	0	0	0	0	0	0	0	0	0	3.5	2.7
4	**Solar Panels**	0	0	0	0	0	0	0.009	0	0	0	0	0	0	0	0.081
5	**Human Nutrition**	0	0	0	0	0	0	0	0	0	0.37	0	0	0	0	3.65
6	**Electricity**	0	0	0	0	0	0	0	0	0	0	0.0009	0	0	0	0.0081
7	**Diesel**	0	0	0	0	0	0	0	0	0	0	0	1.2	0	0	6.6
8	**Fuelwood**	0	0	0	0	0	0	0	0	0	0	0	0	0.75	0	2.25
9	**Human Labor**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.37
10	**Light**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0009
11	**Mechanical Energy**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.2
12	**Process Energy**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.75
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 45 Flow matrix for Trinket Island Energy network

		0	1	2	3	4	5	6	7	Exports	Dissipation
	Imports	0	231.795	453.308	194.521	27.079	109.338	91.658	62.38	0	0
1	**Electric**	0	0	13.178	0.323	0.003	2.218	0.942	0	220.376	0
2	**Industry**	0	0	0	0	0.004	0	0	0	468.812	0
3	**Petrifaction**	0	0	0.721	0	0	1.109	0	0	192.072	0
4	**Agriculture**	0	0	0.145	0	0	0	0	0	26.941	0
5	**Resident**	0	4.371	0	0	0	0	0	0	108.294	0
6	**Business**	0	0.874	0	0	0	0	0	0	92.668	0
7	**Transportation**	0	0	1.464	0	0	0	0	0	60.916	0
		0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0

Figure 46 Flow matrix for Xiamen Energy network

		0	1	2	3	4	Exports	Dissipation
	Imports	0	7.15E+09	1.38E+10	1.21E+10	0	0	0
1	**Energy Exploitation sector**	0	0	6.44E+09	6.65E+08	0	5.00E+07	0
2	**Energy Transformation sector**	0	0	0	1.56E+10	0	1.90E+09	0
3	**Energy Consumption sector**	0	0	0	0	7.90E+06	3.28E+08	0
4	**Energy Recovery sector**	0	0	0	7.90E+06	0	0	0
		0	0	0	0	0	0	0
		0	0	0	0	0	0	0

Figure 47 Flow matrix for 1995 Beijing Energy network

		0	1	2	3	4	Exports	Dissipation
	Imports	0	5.04E+09	1.70E+10	1.52E+10	0	0	0
1	**Energy Exploitation sector**	0	0	4.93E+09	1.11E+08	0	0	0
2	**Energy Transformation sector**	0	0	0	1.66E+10	0	2.65E+09	0
3	**Energy Consumption sector**	0	0	0	0	1.76E+09	5.05E+08	0
4	**Energy Recovery sector**	0	0	4.24E+08	1.33E+09	0	0	0
		0	0	0	0	0	0	0
		0	0	0	0	0	0	0

Figure 48 Flow matrix for 2000 Beijing Energy network

		0	1	2	3	4	Exports	Dissipation
	Imports	0	6.77E+09	1.85E+10	2.36E+10	0	0	0
1	**Energy Exploitation sector**	0	0	6.75E+09	1.68E+07	0	0	0
2	**Energy Transformation sector**	0	0	0	2.94E+10	0	1.08E+09	0
3	**Energy Consumption sector**	0	0	0	0	0	7.52E+08	0
4	**Energy Recovery sector**	0	0	0	0	0	0	0
		0	0	0	0	0	0	0
		0	0	0	0	0	0	0

Figure 49 Flow matrix for 2005 Beijing Energy network

		0	1	2	3	4	Exports	Dissipation
	Imports	0	4.65E+09	2.22E+10	2.88E+10	0	0	0
1	**Energy Exploitation sector**	0	0	4.63E+09	1.09E+07	0	0	0
2	**Energy Transformation sector**	0	0	0	2.88E+10	7.75E+07	1.39E+09	0
3	**Energy Consumption sector**	0	0	0	0	4.81E+07	6.98E+08	0
4	**Energy Recovery sector**	0	0	1.26E+08	0	0	0	0
		0	0	0	0	0	0	0
		0	0	0	0	0	0	0

Figure 50 Flow matrix for 2007 Beijing Energy network

		0	1	2	3	Exports	Dissipation
	Imports	0	7.38E+22	6.23E+23	3.15E+24	0	0
1	**Agricultural Sector**	0	0	3.49E+23	6.99E+22	1.01E+22	0
2	**Industrial Sector**	0	4.14E+21	0	2.41E+23	2.46E+23	0
3	**Domestic Sector**	0	5.96E+23	2.29E+24	0	3.75E+22	0
		0	0	0	0	0	0
		0	0	0	0	0	0

Figure 51 Flow matrix for Beijing Emergy network

		0	1	2	3	Exports	Dissipation
	Imports	0	1.42E+22	3.75E+23	8.29E+23	0	0
1	**Agricultural Sector**	0	0	2.00E+23	7.06E+22	4.99E+21	0
2	**Industrial Sector**	0	5.50E+21	0	1.61E+23	2.53E+23	0
3	**Domestic Sector**	0	8.03E+23	1.64E+24	0	1.36E+22	0
		0	0	0	0	0	0
		0	0	0	0	0	0

Figure 52 Flow matrix for Tianjin Emergy network

		0	1	2	3	Exports	Dissipation
	Imports	0	3.05E+22	1.85E+22	3.78E+24	0	0
1	**Agricultural Sector**	0	0	3.00E+22	3.98E+22	2.62E+22	0
2	**Industrial Sector**	0	1.18E+22	0	5.67E+23	8.94E+23	0
3	**Domestic Sector**	0	6.52E+23	3.11E+24	0	4.62E+22	0
		0	0	0	0	0	0
		0	0	0	0	0	0

Figure 53 Flow matrix for Shanghai Emergy network

		0	1	2	3	Exports	Dissipation
	Imports	0	2.30E+22	1.14E+23	2.15E+23	0	0
1	**Agricultural Sector**	0	0	8.72E+21	1.19E+23	1.49E+21	0
2	**Industrial Sector**	0	4.70E+21	0	1.96E+23	3.65E+22	0
3	**Domestic Sector**	0	8.43E+24	3.29E+24	0	1.70E+22	0
		0	0	0	0	0	0
		0	0	0	0	0	0

Figure 54 Flow matrix for Chongqing Emergy network

		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Exports	Dissipation
	Imports	0	3980	1	146	22	23	787	904	3951	52	1093	11	215	7000000	824	0	0	0
1	**Agriculture**	0	855	0	0	0	0	0	0	0	0	4107	0	0	0	669	0	126	0
2	**Mining**	0	210	1	3562	87	1	2643	16043	37707	282	2243	16450	225	0	72810	5208	0	0
3	**Textile**	0	14	0	612	3	0	89	7	1	97	372	0	0	0	0	5	376	0
4	**Timber Processing and Furniture Manufacturing**	0	1	1	0	101	0	4	3	2	28	16	1	0	0	124	23	312	0
5	**Processing of Petroleum and Coking**	0	46	1	60	4	1	178	533	5736	282	108	86	0	0	73	1129	90	0
6	**Chemistry**	0	111	15	462	60	81	2205	57	86	751	132	22	0	1	157	97	504	0
7	**Non-Metallic Mineral Products**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10387	0	773	0
8	**Smelting and Pressing of Ferrous Metals**	0	0	0	0	0	0	0	0	0	10524	0	0	0	0	872	0	2992	0
9	**Mechanical Industry**	0	0	0	0	0	0	2	1	4	63	1	1	0	0	7	5	72	0
10	**Other Manufacturing**	0	165639	13	12	20	2	251	32	30	215	798	7	4	1	25	269	1652	0
11	**Production and Supply of Electric and Heat Power**	0	36	2	1332	40	1	895	202	1047	1225	489	300	3	29	58	899	0	0
12	**Production and Supply of Gas**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	**Production and Supply of Water**	0	1524222	0	444046	0	0	206000	4315	117228	195400	128628	561274	0	1474231	1000	53910	6173	0
14	**Construction**	0	1658	835	207	136	193	1127	259	2015	2943	176	627	35	69	0	32310	5084	0
15	**Services**	0	109500	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 55 Flow matrix for Suzhou Material network

		0	1	2	3	4	5	6	Exports	Dissipation
	Imports	0	1430	26	831	137	23	0	0	0
1	**Energy production sector**	0	0	0	0	70	420	940	0	0
2	**Water and soil**	0	0	0	0	6	6	14	0	0
3	**Construction sector**	0	0	0	0	35	156	640	0	0
4	**Agriculture sector**	0	0	0	0	0	104	0	168	0
5	**Industry, trade,and service sector**	0	0	0	0	0	0	0	814	0
6	**Domestic Sector**	0	0	0	0	24	105	0	1465	0
		0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0

Figure 56 Flow matrix for Vienna Carbon network

		0	1	2	3	4	5	6	7	8	9	10	11	Exports	Dissipation
	Imports	0	2300	620	4100	0	0	0	0	1500	100	2900	0	0	0
1	**Energy Supply**	0	0	0	0	0	0	0	0	0	450	0	0	0	0
2	**Service**	0	0	0	0	230	0	0	4100	250	0	0	0	0	0
3	**Food Supply**	0	0	4000	0	0	0	0	0	0	0	0	0	66	0
4	**Real Estate**	0	0	0	0	0	0	0	0	0	250	0	230	0	0
5	**Transport**	0	0	0	0	0	0	0	0	0	1700	0	0	0	0
6	**Infrastructure**	0	0	0	0	0	0	0	0	0	1100	0	0	0	0
7	**Households**	0	0	0	0	0	0	0	0	3800	0	0	0	310	0
8	**Waste Management**	0	0	0	0	0	0	0	0	0	74	2700	0	830	0
9	**Air**	0	0	0	0	0	0	0	0	0	0	0	160	3600	0
10	**Water**	0	0	0	0	0	0	0	0	0	0	0	0	5600	0
11	**Land**	0	0	0	0	0	0	0	0	96	60	76	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 57 Flow matrix for Stockholm Nitrogen network

		0	1	2	3	4	5	6	7	8	Exports	Dissipation
	Imports	0	65	240	510	0	0	200	0	120	0	0
1	**Energy Supply**	0	0	0	0	0	0	0	0	0	65	0
2	**Service**	0	0	0	0	23	670	47	0	0	0	0
3	**Food Supply**	0	0	510	0	0	0	0	0	0	0	0
4	**Real Estate**	0	0	0	0	0	0	0	23	0	0	0
5	**Households**	0	0	0	0	0	0	620	0	0	50	0
6	**Waste Management**	0	0	0	0	0	0	0	0	34	860	0
7	**Land**	0	0	0	0	0	0	14	0	11	0	0
8	**Water**	0	0	0	0	0	0	0	0	0	170	0
		0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0

Figure 58 Flow matrix for Stockholm Phosphorus network

		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Exports	Dissipation
	Imports	0	8.26	0.25	295.7	10.6	0	0	0	0	0	0	0	0	0	0	0	13.31	0	0
1	**Household**	0	0	0	0	1.14	0	0	0	0	0	0	5.22	19.4	8.55	0	0	9.3	47.02	0
2	**Pets**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0.02	0
3	**Industry**	0	10.97	0.27	0	8.98	3.13	0.82	0.1	0.94	3.61	29.72	1.52	5.65	94.06	0	0	126.6	9.3	0
4	**Animal Husbandry**	0	19.57	0	0	0	0	0	0	0	0	0	0	7.96	2.27	0	0	10.97	15.98	0
5	**Crop Cultivation**	0	50.21	0	0	35.94	0	3.06	0	0	0	0	0	0	2.85	0	0	24.98	0	0
6	**Aquaculture**	0	1.62	0	0	0.09	0	0	0	0	0	0	0	1.97	0.19	0	0	0	0.01	0
7	**Forestry**	0	0	0	0	0	0	0	0	0	0	0	0	0	0.09	0	0	0	0.01	0
8	**Service**	0	0	0	0	0	0	0	0	0	0	0	0	0	0.85	0	0	0	0.09	0
9	**Construction**	0	0	0	0	0	0	0	0	0	0	0	0	0	3.29	0	0	0	0.32	0
10	**Transportation**	0	0	0	0	0	0	0	0	0	0	0	0	0	25.27	0	0	0	4.45	0
11	**Sewage treatment**	0	0	0	0	0	0	0	0	0	0	0	0	4.04	2.7	0	0	0	0	0
12	**Surface water**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.57	51.24	0
13	**Atmosphere**	0	0	0	0	0	10.19	0	0	0	0	0	0	1.45	0	46.77	0.13	4.01	167.41	0
14	**Forest**	0	0	0	0	0	0	0	0	0	0	0	0	1.2	8.18	0	0	0	37.39	0
15	**Grassland**	0	0	0	0	0	0	0	0	0	0	0	0	0.03	3.54	0	0	0	0	0
16	**Farmland**	0	0	0	0	0	50.21	0	0	0	0	0	0	11.11	78.12	0	0	0	51.29	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 59 Flow matrix for 1996 Beijing Nitrogen network

		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Exports	Dissipation
	Imports	0	20.64	0.27	245.3	14.99	0	0	0	0	0	0	0	0	0	0	0	56.99	0	0
1	**Household**	0	0	0	0	1.61	0	0	0	0	0	0	12.07	18.56	9.59	0	0	9.95	34.34	0
2	**Pets**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.54	0	0	0
3	**Industry**	0	12.27	0.27	0	11.45	2.24	0.79	0.13	1.51	3.22	42.95	1.74	2.68	86.13	0	0	70.35	9.56	0
4	**Animal Husbandry**	0	24.03	0	0	0	0	0	0	0	0	0	0	12.39	2.01	0	0	18.32	22.13	0
5	**Crop Cultivation**	0	27.63	0	0	50.75	0	2.94	0	0	0	0	0	0	2.02	0	0	14.59	0	0
6	**Aquaculture**	0	1.55	0	0	0.08	0	0	0	0	0	0	0	1.9	0.18	0	0	0	0.02	0
7	**Forestry**	0	0	0	0	0	0	0	0	0	0	0	0	0	0.12	0	0	0	0.01	0
8	**Service**	0	0	0	0	0	0	0	0	0	0	0	0	0	1.36	0	0	0	0.15	0
9	**Construction**	0	0	0	0	0	0	0	0	0	0	0	0	0	2.89	0	0	0	0.33	0
10	**Transportation**	0	0	0	0	0	0	0	0	0	0	0	0	0	36.51	0	0	0	6.44	0
11	**Sewage treatment**	0	0	0	0	0	0	0	0	0	0	0	0	8.28	5.52	0	0	0	0.01	0
12	**Surface water**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.68	55.19	0
13	**Atmosphere**	0	0	0	0	0	11.54	0	0	0	0	0	0	1.42	0	44.57	1.74	3.96	169.87	0
14	**Forest**	0	0	0	0	0	0	0	0	0	0	0	0	1.14	7.79	0	0	0	35.64	0
15	**Grassland**	0	0	0	0	0	0	0	0	0	0	0	0	0.11	3.59	0	0	0	0	0
16	**Farmland**	0	0	0	0	0	27.63	0	0	0	0	0	0	10.39	75.39	0	0	0	62.43	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 60 Flow matrix for 2000 Beijing Nitrogen network

		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Exports	Dissipation
	Imports	0	43.29	0.3	253	20.04	0	0	0	0	0	0	0	0	0	0	0	62.26	0	0
1	**Household**	0	0	0	0	2.13	0	0	0	0	0	0	21.56	18.44	5.53	0	0	11.83	58.87	0
2	**Pets**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.6	0	0	0
3	**Industry**	0	24.29	0.3	0	15.18	1.85	0.73	0.25	4.83	3.97	77.26	1.35	1.15	68.57	0	0	41.21	12.1	0
4	**Animal Husbandry**	0	37.58	0	0	0	0	0	0	0	0	0	0	20.16	2.35	0	0	35.19	9.9	0
5	**Crop Cultivation**	0	11.81	0	0	67.76	0	2.63	0	0	0	0	0	0	1.57	0	0	5.37	0	0
6	**Aquaculture**	0	1.39	0	0	0.07	0	0	0	0	0	0	0	1.69	0.18	0	0	0	0.03	0
7	**Forestry**	0	0	0	0	0	0	0	0	0	0	0	0	0	0.22	0	0	0	0.03	0
8	**Service**	0	0	0	0	0	0	0	0	0	0	0	0	0	4.1	0	0	0	0.73	0
9	**Construction**	0	0	0	0	0	0	0	0	0	0	0	0	0	3.38	0	0	0	0.59	0
10	**Transportation**	0	0	0	0	0	0	0	0	0	0	0	0	0	65.67	0	0	0	11.59	0
11	**Sewage treatment**	0	0	0	0	0	0	0	0	0	0	0	0	13.74	9.16	0	0	0	0.01	0
12	**Surface water**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.97	63.96	0
13	**Atmosphere**	0	0	0	0	0	7.4	0	0	0	0	0	0	1.39	0	44.51	2.19	4.01	166.74	0
14	**Forest**	0	0	0	0	0	0	0	0	0	0	0	0	1.14	7.78	0	0	0	35.59	0
15	**Grassland**	0	0	0	0	0	0	0	0	0	0	0	0	0.14	3.59	0	0	0	0	0
16	**Farmland**	0	0	0	0	0	11.81	0	0	0	0	0	0	7.08	54.14	0	0	0	87.81	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 61 Flow matrix for 2004 Beijing Nitrogen network

		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Exports	Dissipation
	Imports	0	44.3	0.35	281	11.6	0	0	0	0	0	0	0	0	0	0	0	77.1	0	0
1	**Household**	0	0	0	0	1.25	0	0	0	0	0	0	22.49	6.01	30.94	0	0	13.44	69.21	0
2	**Pets**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.71	0	0	0
3	**Industry**	0	39.96	0.35	0	9.68	2.28	0.65	0.36	9.42	4.84	134.9	0.88	0.23	52.05	0	0	12.53	12.89	0
4	**Animal Husbandry**	0	29.73	0	0	0	0	0	0	0	0	0	0	10.82	2.13	0	0	16.62	2.73	0
5	**Crop Cultivation**	0	28.09	0	0	39.43	0	2.39	0	0	0	0	0	0	1.94	0	0	8.6	0	0
6	**Aquaculture**	0	1.26	0	0	0.07	0	0	0	0	0	0	0	1.54	0.15	0	0	0	0.02	0
7	**Forestry**	0	0	0	0	0	0	0	0	0	0	0	0	0	0.31	0	0	0	0.05	0
8	**Service**	0	0	0	0	0	0	0	0	0	0	0	0	0	8.01	0	0	0	1.41	0
9	**Construction**	0	0	0	0	0	0	0	0	0	0	0	0	0	4.12	0	0	0	0.72	0
10	**Transportation**	0	0	0	0	0	0	0	0	0	0	0	0	0	107.9	0	0	0	26.98	0
11	**Sewage treatment**	0	0	0	0	0	0	0	0	0	0	0	0	14.02	9.34	0	0	0	0.01	0
12	**Surface water**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.89	40.35	0
13	**Atmosphere**	0	0	0	0	0	7.43	0	0	0	0	0	0	1.37	0	44.42	1.67	3.93	214.77	0
14	**Forest**	0	0	0	0	0	0	0	0	0	0	0	0	1.14	7.77	0	0	0	35.51	0
15	**Grassland**	0	0	0	0	0	0	0	0	0	0	0	0	0.12	4.25	0	0	0	0	0
16	**Farmland**	0	0	0	0	0	28.09	0	0	0	0	0	0	5.99	44.68	0	0	0	54.35	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 62 Flow matrix for 2008 Beijing Nitrogen network

		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Exports	Dissipation
	Imports	0	67	0.43	275.4	11.2	0	0	0	0	0	0	0	0	0	0	0	81.9	0	0
1	**Household**	0	0	0	0	1.2	0	0	0	0	0	0	30.82	6.31	40.37	0	0	18.8	75.89	0
2	**Pets**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.83	0	0.01	0
3	**Industry**	0	51.97	0.41	0	8.7	1.94	0.15	0.64	9.73	5.18	165.1	0.73	0.15	34.46	0	0	5.23	0	0
4	**Animal Husbandry**	0	29.05	0	0	0	0	0	0	0	0	0	0	10.39	1.53	0	0	16.08	2.1	0
5	**Crop Cultivation**	0	24.05	0	0	37.98	0	2.51	0	0	0	0	0	0	1.65	0	0	7.59	9.9	0
6	**Aquaculture**	0	1.32	0	0	0.07	0	0	0	0	0	0	0	1.61	0.13	0	0	0	0	0
7	**Forestry**	0	0	0	0	0	0	0	0	0	0	0	0	0	0.54	0	0	0	0.1	0
8	**Service**	0	0	0	0	0	0	0	0	0	0	0	0	0	8.27	0	0	0	1.46	0
9	**Construction**	0	0	0	0	0	0	0	0	0	0	0	0	0	4.41	0	0	0	0.77	0
10	**Transportation**	0	0	0	0	0	0	0	0	0	0	0	0	0	132.1	0	0	0	33.03	0
11	**Sewage treatment**	0	0	0	0	0	0	0	0	0	0	0	0	18.93	12.62	0	0	0	0	0
12	**Surface water**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.83	45.04	0
13	**Atmosphere**	0	0	0	0	0	6.15	0	0	0	0	0	0	1.34	0	44.51	1.68	3.75	235.22	0
14	**Forest**	0	0	0	0	0	0	0	0	0	0	0	0	1.14	7.78	0	0	0	35.59	0
15	**Grassland**	0	0	0	0	0	0	0	0	0	0	0	0	0.13	4.97	0	0	0	0	0
16	**Farmland**	0	0	0	0	0	75.59	0	0	0	0	0	0	5.87	43.81	0	0	0	8.91	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 63 Flow matrix for 2012 Beijing Nitrogen network

		0	1	2	3	4	5	6	7	8	9	10	Exports	Dissipation
	Imports	0	20	82	12	42	29	0	105	18	0	14	0	0
1	**Rivers**	0	0	0	0	0	0	0	0	0	0	0	26	0
2	**Forests and Agriculture**	0	3	0	0	5	0	0	0	85	0	0	0	0
3	**Poultry**	0	0	11	0	0	0	0	0	1	0	0	0	0
4	**Dairy**	0	0	0	0	0	0	0	0	16	0	0	31	0
5	**Meat Products Outlets**	0	0	0	0	0	0	11	0	7	0	0	11	0
6	**Waste Dumps**	0	0	0	0	0	0	0	0	0	0	0	0	203
7	**Paper and Pulp Industry**	0	0	0	0	0	0	68	0	0	0	0	37	0
8	**Population Centre**	0	3	0	0	0	0	51	0	0	74	0	0	0
9	**Sewage Treatment Plant**	0	0	0	0	0	0	70	0	0	0	0	4	0
10	**Fish Industry**	0	0	0	0	0	0	3	0	1	0	0	10	0
		0	0	0	0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 64 Flow matrix for Gavle Phosphorus network

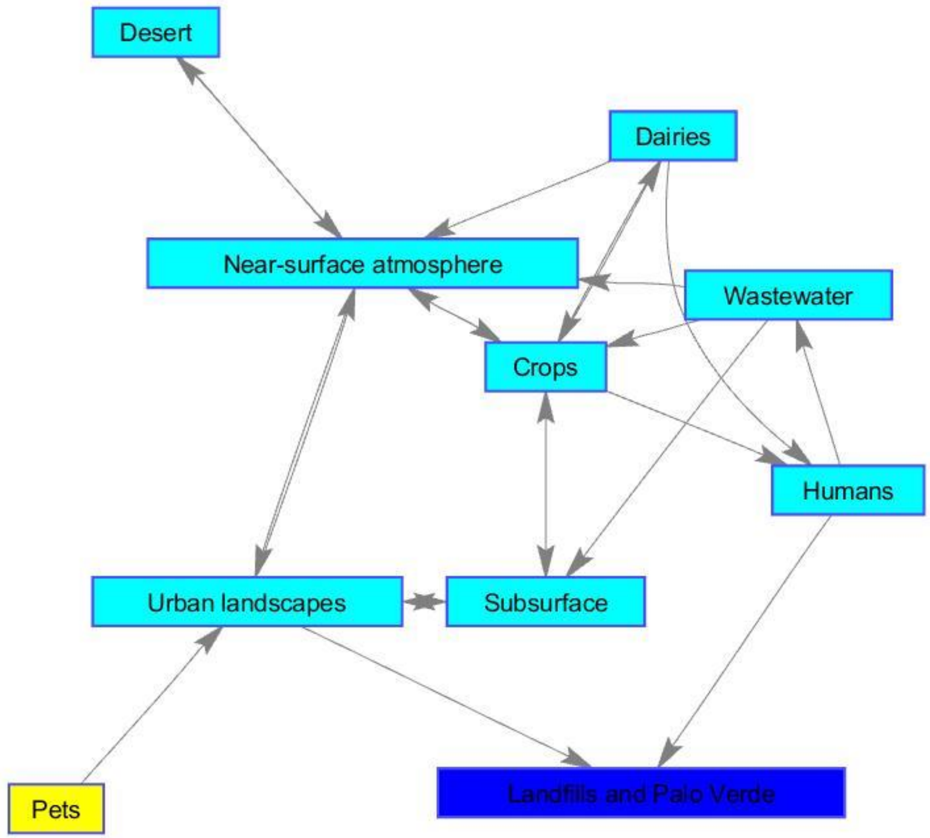


Figure 65 Network configuration for Central Arizona-Phoenix Nitrogen network

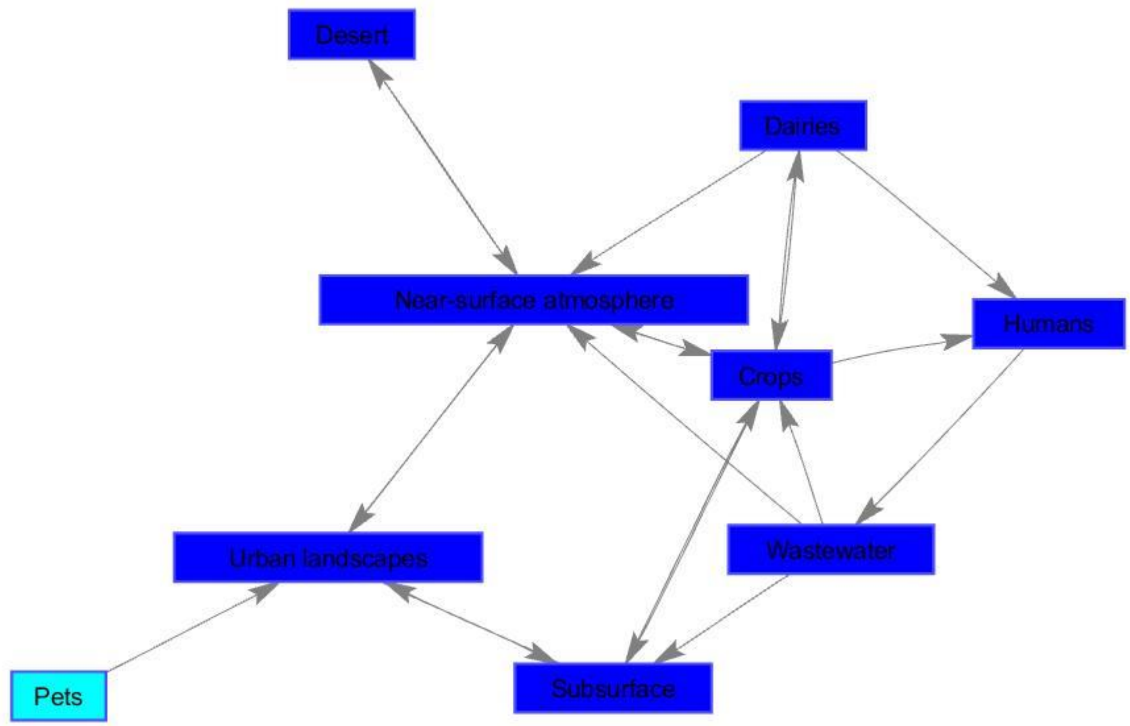


Figure 66 Network configuration for Central Arizona-Phoenix Nitrogen network with Landfill actor

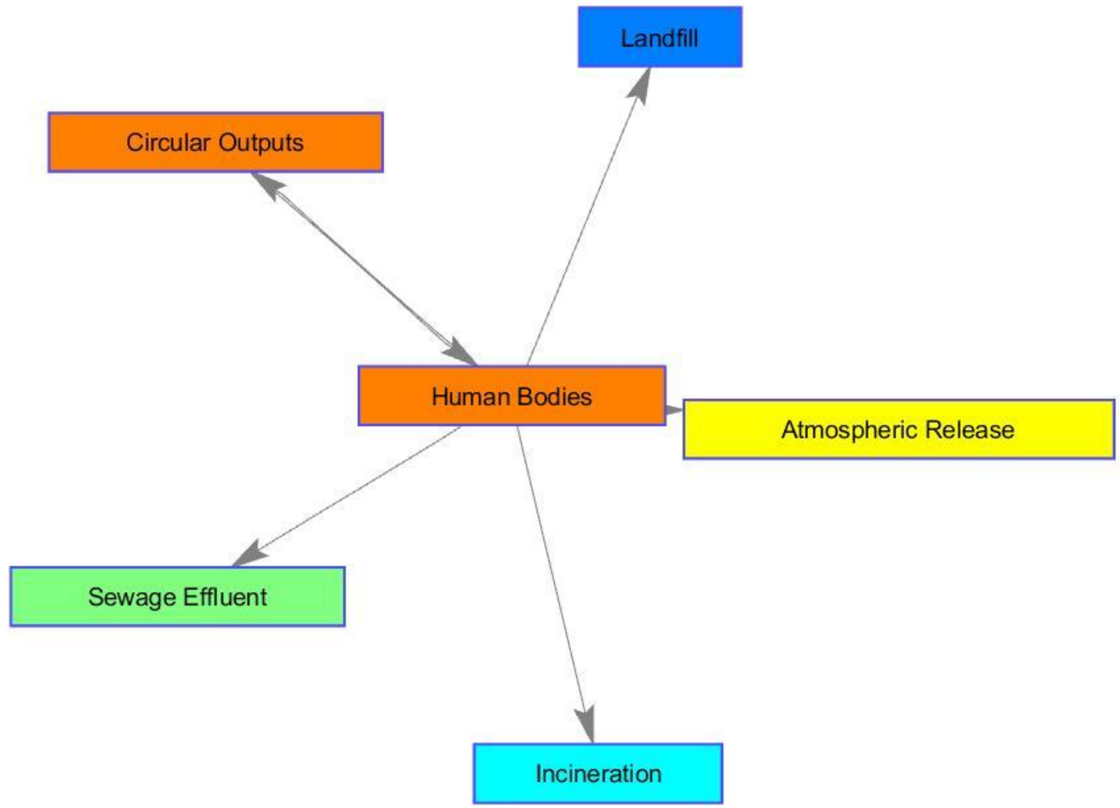


Figure 67 Network configuration for 1990, 2001, and 2004 Toronto Nitrogen networks

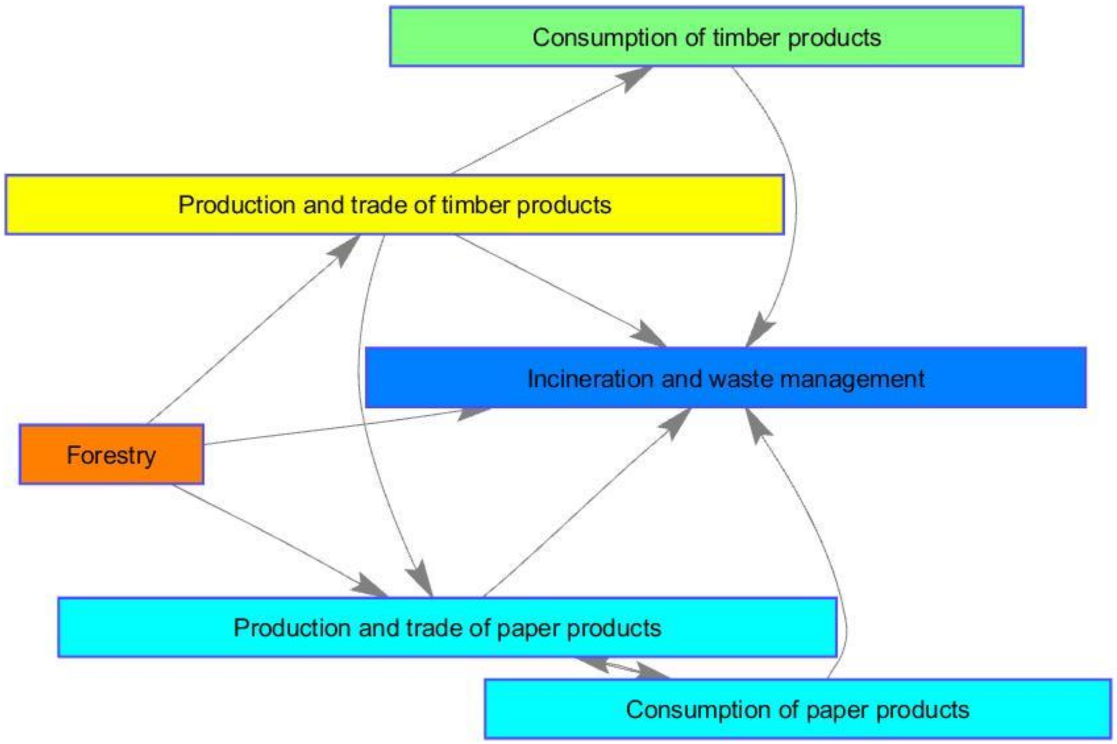


Figure 68 Network configuration for baseline and scenarios 1 Swiss Lowlands Timber networks

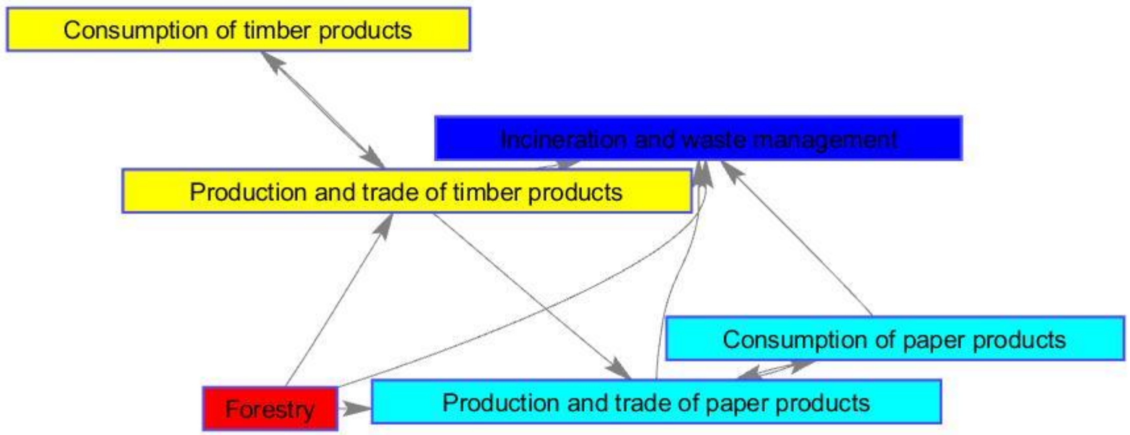


Figure 69 Network configuration for scenario 2 Swiss Lowlands Timber network

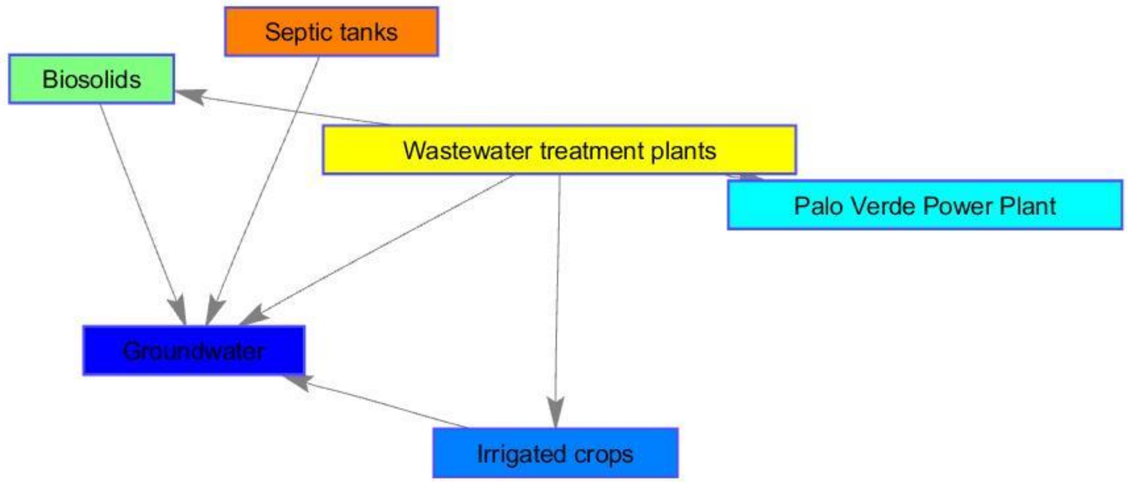


Figure 70 Network configuration for Central Arizona-Phoenix Wastewater Nitrogen network

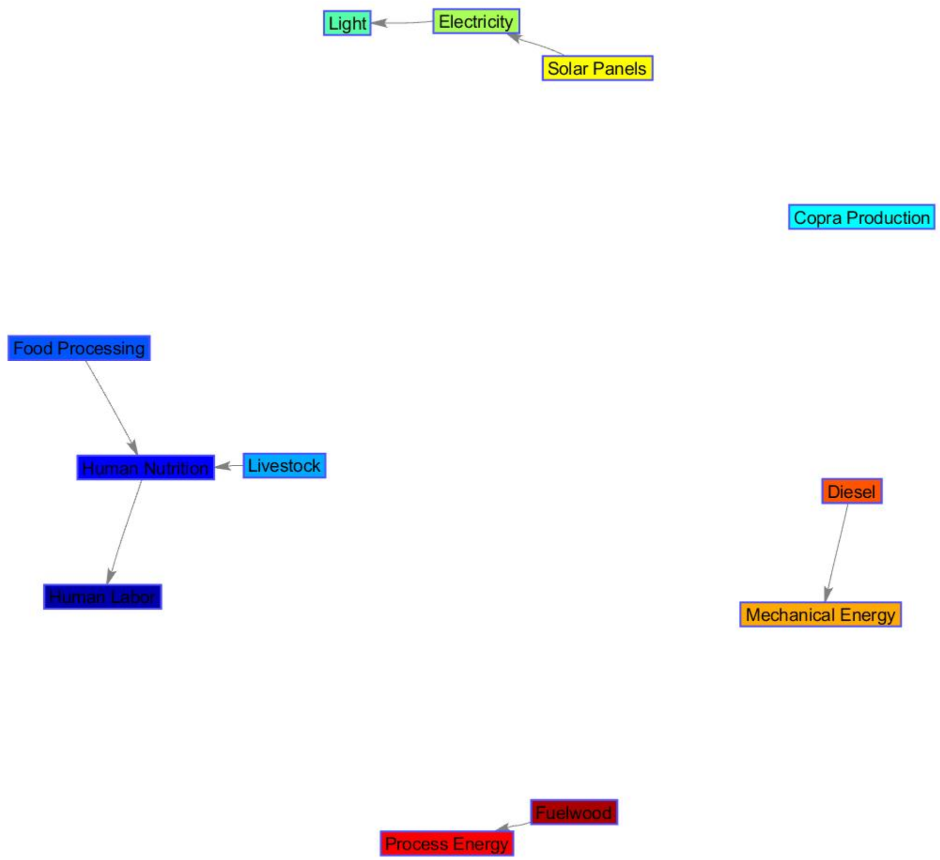


Figure 71 Network configuration for Trinket Island Energy network

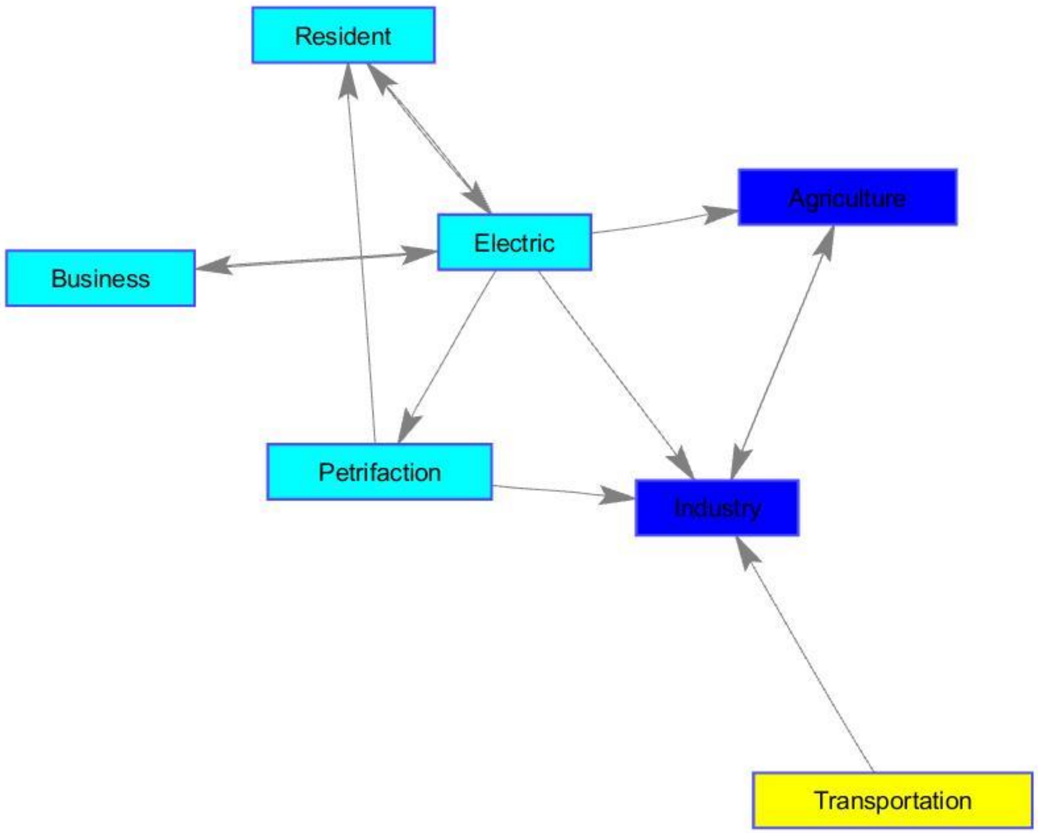


Figure 72 Network configuration for Xiamen Energy network

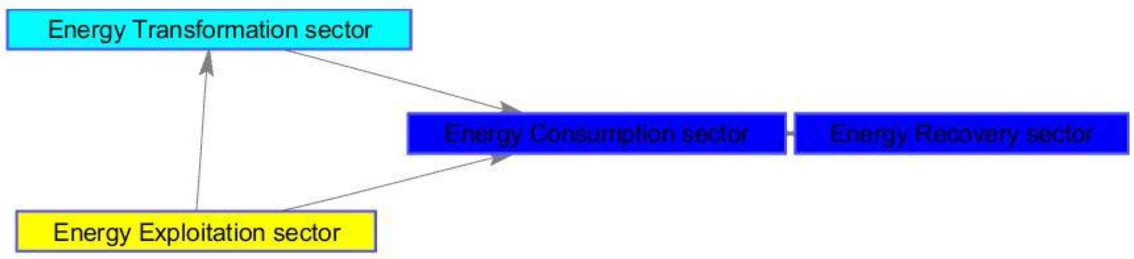


Figure 73 Network configuration for 1995 Beijing Energy network

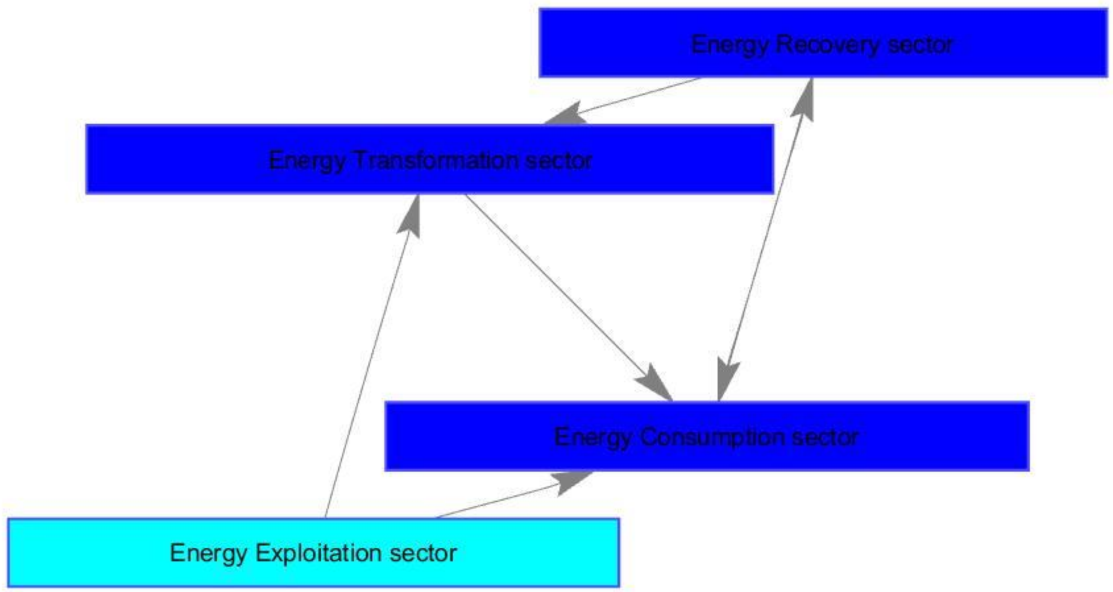


Figure 74 Network configuration for 2000 and 2007 Beijing Energy networks

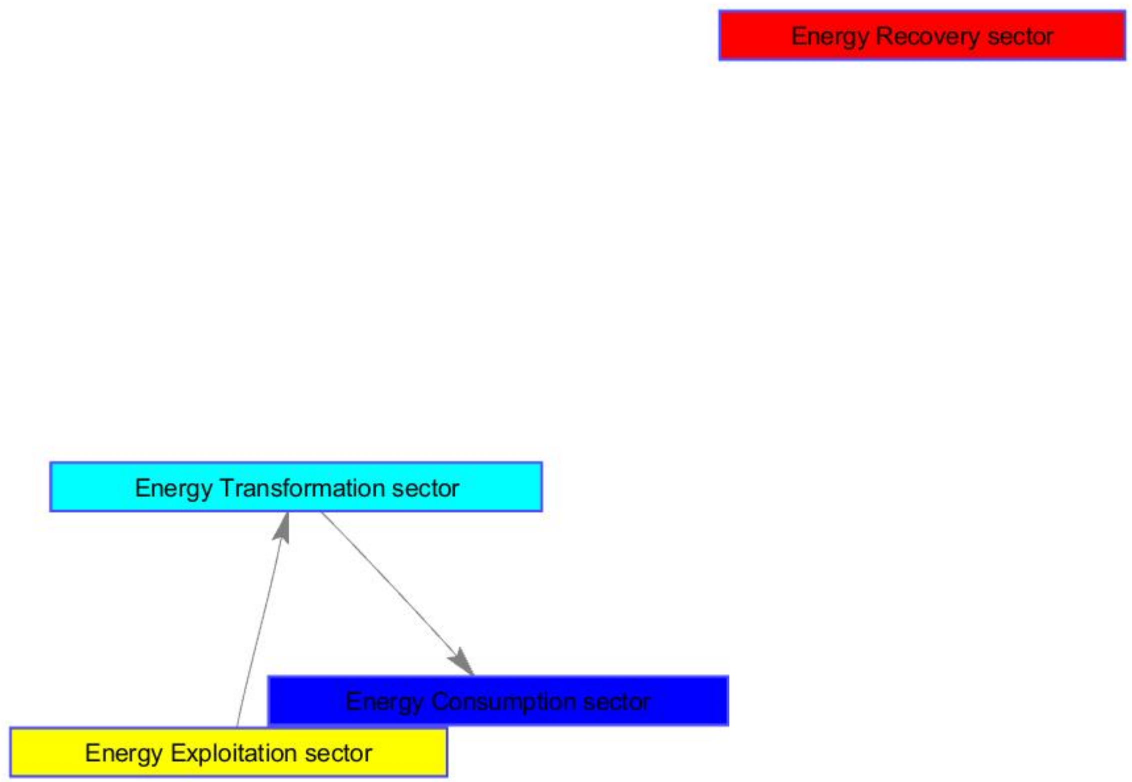


Figure 75 Network configuration for 2005 Beijing Energy network

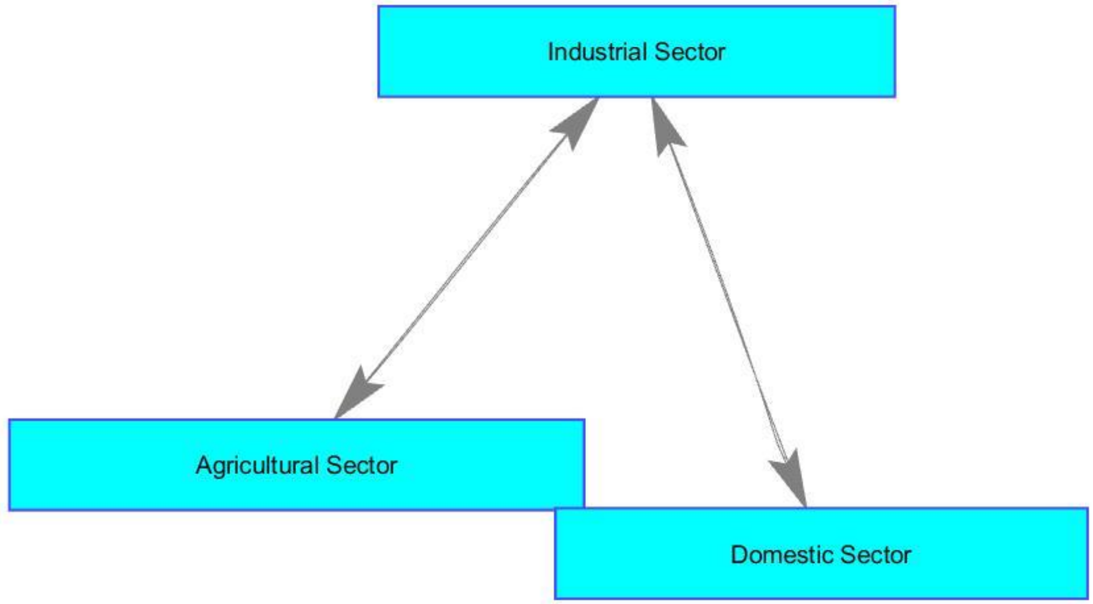


Figure 76 Network configuration for Beijing, Tianjin, Shanghai, and Chongqing Emergy networks

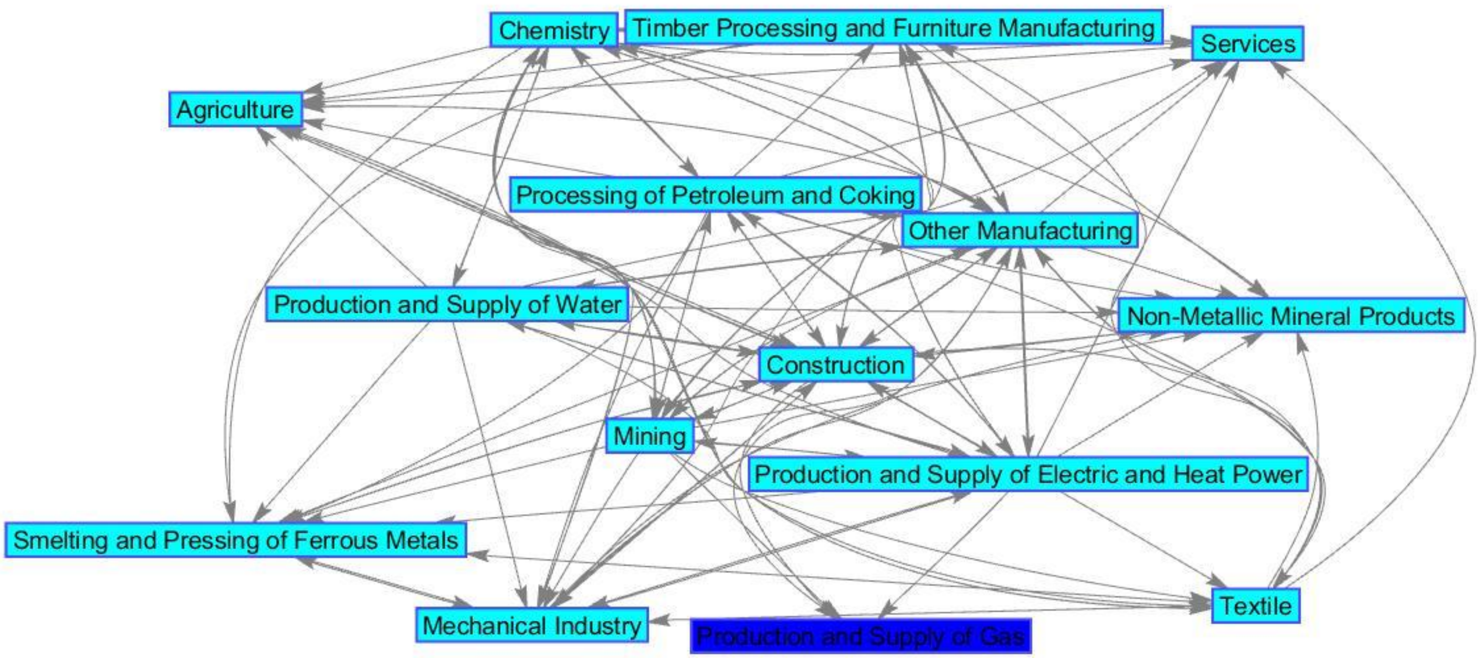


Figure 77 Network configuration for Suzhou Material network

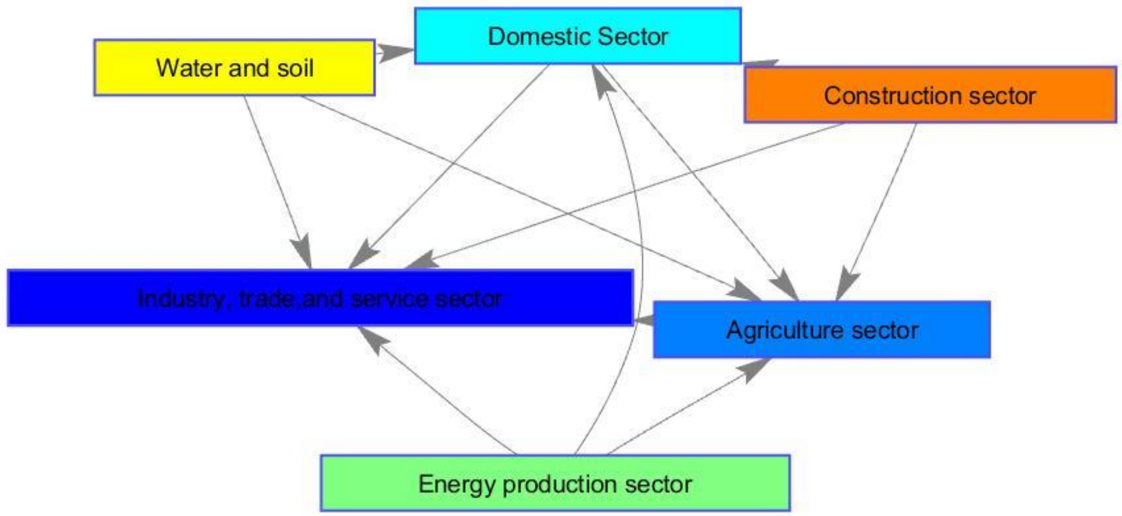


Figure 78 Network configuration for Vienna Carbon network

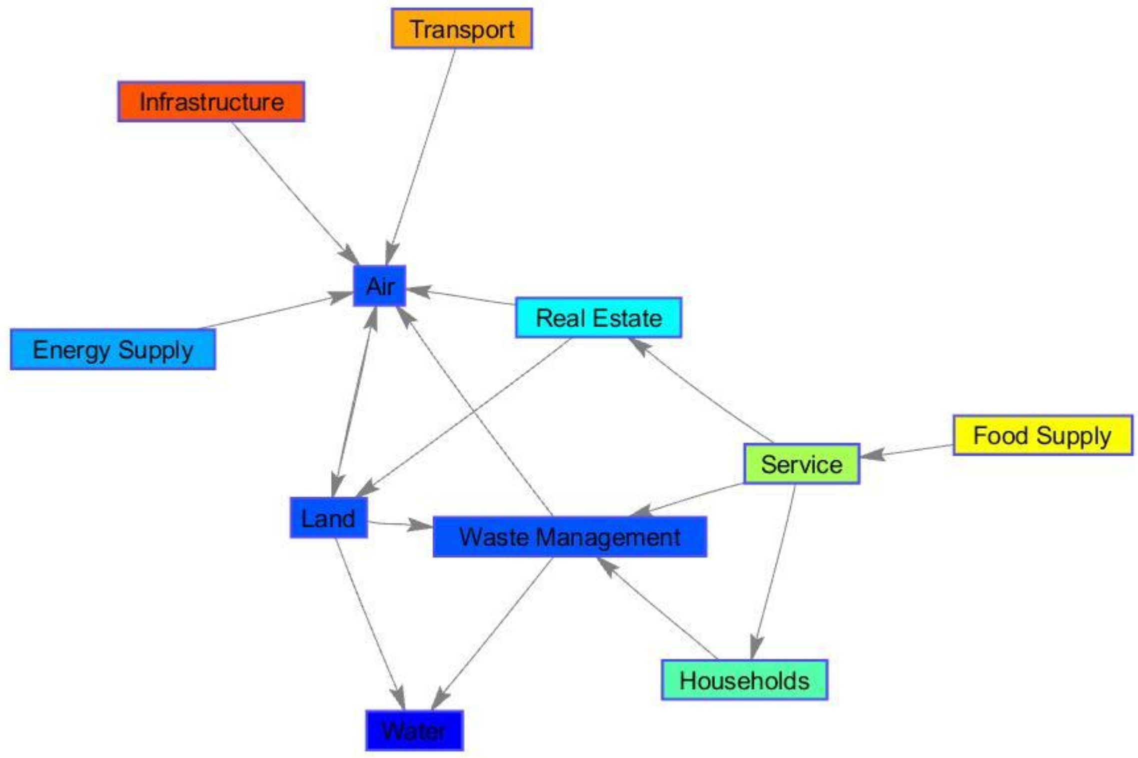


Figure 79 Network configuration for Stockholm Nitrogen network

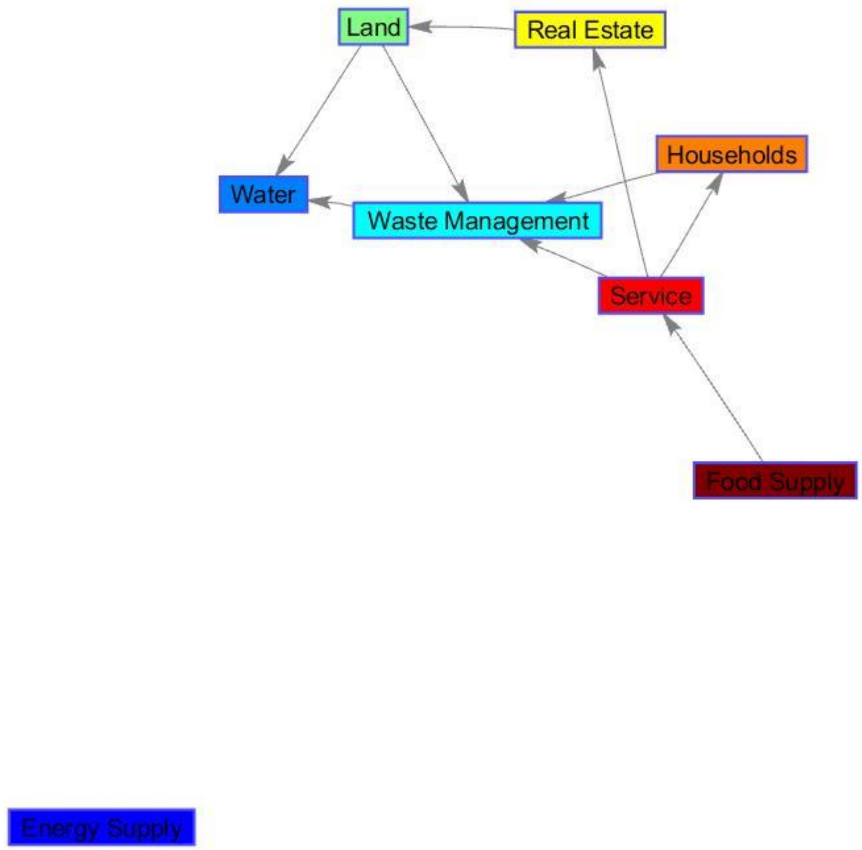


Figure 80 Network configuration for Stockholm Phosphorus network

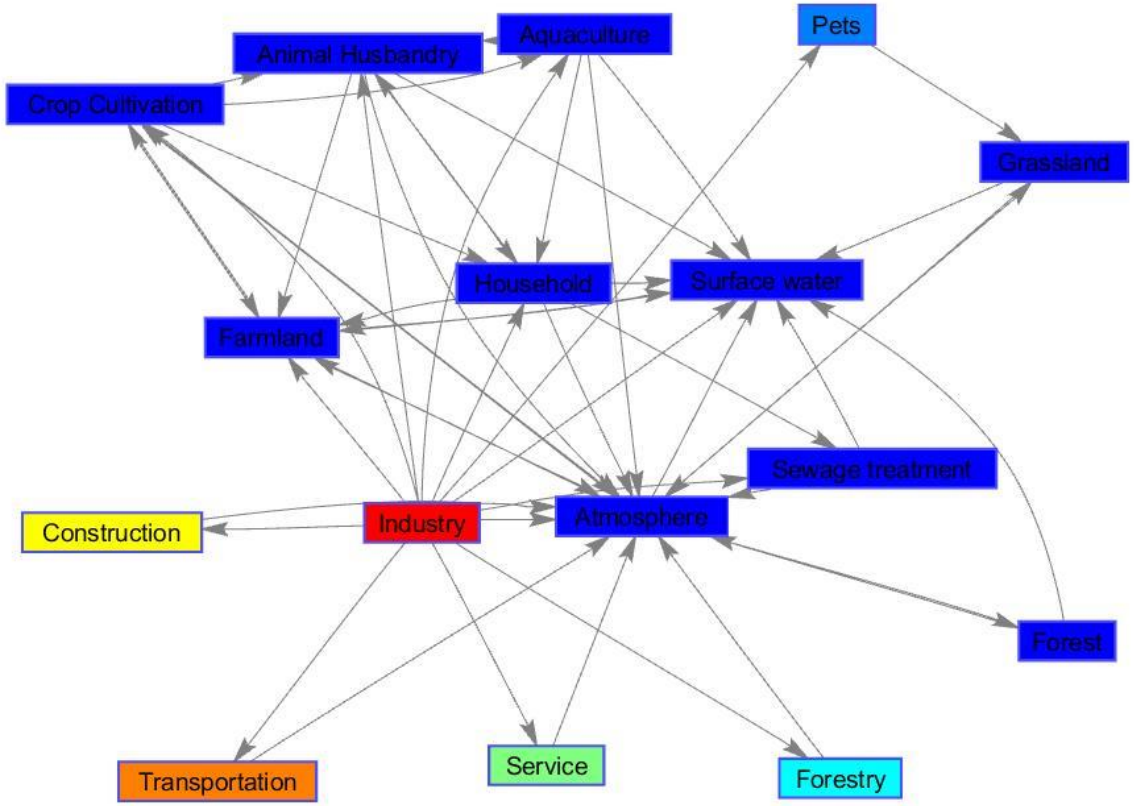


Figure 81 Network configuration for 1996, 2000, 2004, 2008, and 2012 Beijing Nitrogen networks

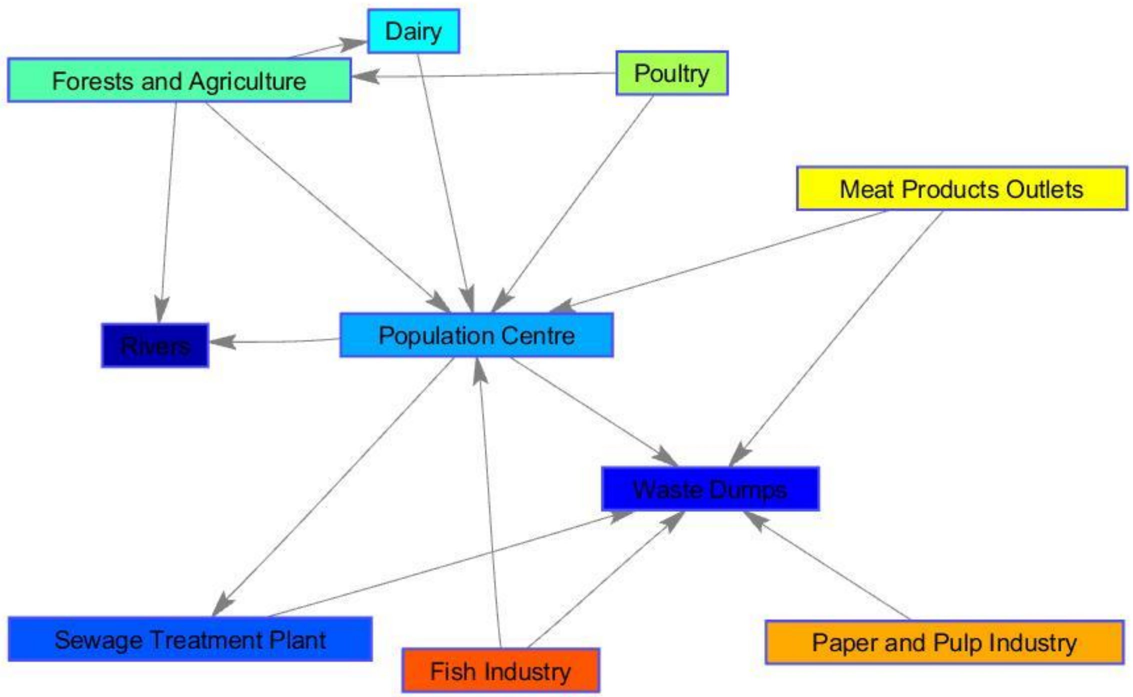


Figure 82 Network configuration for Gavle Phosphorus network

Table 46 Structural ENA metrics for UIEs

Network	λ_{max}	L_D	P_R	G	V	N	L	$n_{predators}$	n_{prey}	C	P_S
Central Arizona-Phoenix Nitrogen	2.519	2.200	1.000	2.444	2.444	10	22	9	9	0.220	0.333
Central Arizona-Phoenix Nitrogen no Landfill	2.519	2.222	1.125	2.500	2.222	9	20	8	9	0.247	0.375
Toronto Nitrogen 1990	1.000	1.000	0.333	1.000	3.000	6	6	6	2	0.167	1.000
Toronto Nitrogen 2001	1.000	1.000	0.333	1.000	3.000	6	6	6	2	0.167	1.000
Toronto Nitrogen 2004	1.000	1.000	0.333	1.000	3.000	6	6	6	2	0.167	1.000
Swiss Lowlands Timber	1.000	1.833	1.000	2.200	2.200	6	11	5	5	0.306	0.600
Swiss Lowlands Timber Scenario 1	1.000	1.833	1.000	2.200	2.200	6	11	5	5	0.306	0.600
Swiss Lowlands Timber Scenario 2	1.000	1.833	1.000	2.200	2.200	6	11	5	5	0.306	0.400
Central Arizona-Phoenix Wastewater Nitrogen	0	1.167	1.000	1.750	1.750	6	7	4	4	0.194	0.750
Trinket Island Energy	0	0.583	1.167	1.167	1.000	12	7	6	7	0.049	0.833
Xiamen Energy	1.618	1.714	1.167	2.000	1.714	7	12	6	7	0.245	0.333
Beijing Energy 1995	1.000	1.250	1.333	1.667	1.250	4	5	3	4	0.313	0.667
Beijing Energy 2000	1.325	1.500	1.333	2.000	1.500	4	6	3	4	0.375	0.333
Beijing Energy 2005	0.000	0.750	1.000	1.500	1.500	4	3	2	2	0.188	0.500
Beijing Energy 2007	1.325	1.500	1.333	2.000	1.500	4	6	3	4	0.375	0
Beijing Emergy	2.000	2.000	1.000	2.000	2.000	3	6	3	3	0.667	0
Tianjin Emergy	2.000	2.000	1.000	2.000	2.000	3	6	3	3	0.667	0
Shanghai Emergy	2.000	2.000	1.000	2.000	2.000	3	6	3	3	0.667	0
Chongqing Emergy	2.000	2.000	1.000	2.000	2.000	3	6	3	3	0.667	0
Suzhou Material	8.771	8.733	0.933	8.733	9.357	15	131	15	14	0.582	0
Vienna Carbon	0	2.000	1.667	4.000	2.400	6	12	3	5	0.333	0
Stockholm Nitrogen	1.325	1.455	1.429	2.286	1.600	11	16	7	10	0.132	0.429
Stockholm Phosphorus	0.000	1.125	1.000	1.500	1.500	8	9	6	6	0.141	0.667
Beijing Nitrogen 1996	3.288	3.188	1.067	3.400	3.188	16	51	15	16	0.199	0.400
Beijing Nitrogen 2000	3.288	3.188	1.067	3.400	3.188	16	51	15	16	0.199	0.400
Beijing Nitrogen 2004	3.288	3.188	1.067	3.400	3.188	16	51	15	16	0.199	0.400
Beijing Nitrogen 2008	3.288	3.188	1.067	3.400	3.188	16	51	15	16	0.199	0.400
Beijing Nitrogen 2012	3.288	3.188	1.067	3.400	3.188	16	51	15	16	0.199	0.400
Gavle Phosphorus	0	1.500	1.333	2.500	1.875	10	15	6	8	0.150	0.500

Table 47 Structural ENA metrics for Food Webs

Network	λ_{max}	L_D	P_R	G	V	N	L	$n_{predators}$	n_{prey}	C	P_S
Mangroves (dry)	14.168	14.245	1.056	15.045	14.245	94	1339	89	94	0.152	0.045
Mangroves (wet)	14.160	14.255	1.056	15.056	14.255	94	1340	89	94	0.152	0.045
Middle Atlantic Bight	11.548	11.719	1.032	12.097	11.719	32	375	31	32	0.366	0.000
Southern New England Bight	11.490	11.455	1.031	11.813	11.455	33	378	32	33	0.347	0.000
Georges Bank	11.345	10.968	1.033	11.333	10.968	31	340	30	31	0.354	0.000
Gulf of Maine	11.101	10.710	1.033	11.067	10.710	31	332	30	31	0.345	0.000
Graminoids (dry)	11.058	12.015	1.048	12.587	12.015	66	793	63	66	0.182	0.063
Graminoids (wet)	11.058	12.015	1.048	12.587	12.015	66	793	63	66	0.182	0.063
Florida Bay (dry)	11.012	15.752	1.126	17.739	15.752	##	1969	111	125	0.126	0.027
Florida Bay (wet)	10.965	15.504	1.126	17.459	15.504	##	1938	111	125	0.124	0.027
Lake Oneida (pre-ZM)	10.920	16.486	1.138	18.769	16.486	74	1220	65	74	0.223	0
Lake Oneida (post-ZM)	10.868	16.513	1.134	18.731	16.513	76	1255	67	76	0.217	0
Bay of Quinte (pre-ZM)	9.157	16.913	1.111	18.792	16.913	80	1353	72	80	0.211	0
Bay of Quinte (post-ZM)	8.527	15.622	1.121	17.515	15.622	74	1156	66	74	0.211	0
Cypress (wet)	7.058	8.147	1.214	9.893	8.147	68	554	56	68	0.120	0.089
Cypress (dry)	6.846	8.015	1.214	9.732	8.015	68	545	56	68	0.118	0.089
Sylt-Romo Bight	6.720	4.678	1.054	4.929	4.678	59	276	56	59	0.079	0.143
Narragansett Bay	5.990	4.938	1.067	5.267	4.938	32	158	30	32	0.154	0.100
Neuse Estuary (late summer 1998)	4.089	3.400	1.077	3.923	3.643	30	102	26	28	0.113	0.115
Neuse Estuary (early summer 1998)	3.871	2.567	1.091	3.500	3.208	30	77	22	24	0.086	0.182
Neuse Estuary (early summer 1997)	3.838	2.733	1.091	3.727	3.417	30	82	22	24	0.091	0.136
St. Marks Seagrass, site 1 (Feb.)	3.831	4.275	1.024	5.317	5.190	51	218	41	42	0.084	0.122
St. Marks Seagrass, site 2 (Jan.)	3.732	3.549	1.000	5.171	5.171	51	181	35	35	0.070	0.114
Northern Benguela Upwelling	3.728	5.000	1.200	6.000	5.000	24	120	20	24	0.208	0.150
St. Marks Seagrass, site 4 (Feb.)	3.719	3.980	1.105	5.342	4.833	51	203	38	42	0.078	0.132
St. Marks Seagrass, site 1 (Jan.)	3.679	3.863	1.000	5.184	5.184	51	197	38	38	0.076	0.132
St. Marks Seagrass, site 2 (Feb.)	3.675	3.941	1.026	5.154	5.025	51	201	39	40	0.077	0.128
Neuse Estuary (late summer 1998)	3.650	2.867	1.087	3.739	3.440	30	86	23	25	0.096	0.174
St. Marks Seagrass, site 3 (Jan.)	3.422	2.490	1.111	4.704	4.233	51	127	27	30	0.049	0.111
Bothnian Sea	2.808	2.833	1.200	3.400	2.833	12	34	10	12	0.236	0.200
Bothnian Bay	2.679	2.667	1.200	3.200	2.667	12	32	10	12	0.222	0.200

Table 48 Flow-based ENA metrics for UIEs

Network	FCI	MPL	AMI	ASC	DC	Φ	TST_P	Alpha	R	H
Central Arizona-Phoenix Nitrogen	0.182	2.676	1.377	4.19E+02	1.37E+03	9.47E+02	2.44E+02	0.307	0.523	4.487
Central Arizona-Phoenix Nitrogen no Landfill	0.188	2.596	1.338	4.08E+02	1.37E+03	9.59E+02	2.37E+02	0.298	0.521	4.487
Toronto Nitrogen 1990	0.002	1.683	1.271	4.74E+01	1.10E+02	6.28E+01	2.34E+01	0.430	0.524	2.955
Toronto Nitrogen 2001	0.029	1.934	1.300	6.65E+01	1.58E+02	9.15E+01	3.22E+01	0.421	0.526	3.090
Toronto Nitrogen 2004	0.013	1.837	1.294	6.31E+01	1.43E+02	7.96E+01	3.05E+01	0.442	0.521	2.928
Swiss Lowlands Timber	0.152	3.758	2.000	3.89E+03	6.70E+03	2.81E+03	1.58E+03	0.580	0.456	3.448
Swiss Lowlands Timber Scenario 1	0.378	5.261	2.174	4.92E+03	7.33E+03	2.41E+03	1.95E+03	0.671	0.386	3.240
Swiss Lowlands Timber Scenario 2	0.164	3.132	1.811	5.12E+03	9.90E+03	4.78E+03	2.46E+03	0.517	0.492	3.501
Central Arizona-Phoenix Wastewater Nitrogen	0	1.394	1.314	4.76E+01	7.90E+01	3.14E+01	2.42E+01	0.603	0.440	2.181
Trinket Island Energy	0	1.135	1.313	1.09E+02	3.01E+02	1.92E+02	4.41E+01	0.363	0.531	3.617
Xiamen Energy	0	1.022	0.951	2.25E+03	8.15E+03	5.91E+03	1.20E+03	0.276	0.513	3.447
Beijing Energy 1995	0	1.686	0.506	2.93E+10	1.44E+11	1.15E+11	5.57E+10	0.203	0.467	2.488
Beijing Energy 2000	0.031	1.675	0.616	4.04E+10	1.72E+11	1.31E+11	6.24E+10	0.235	0.491	2.619
Beijing Energy 2005	0	1.738	0.471	4.10E+10	1.94E+11	1.53E+11	8.51E+10	0.211	0.474	2.229
Beijing Energy 2007	0.002	1.605	0.391	3.57E+10	1.97E+11	1.62E+11	8.93E+10	0.181	0.446	2.157
Beijing Emergy	1.000	1.923	0.741	5.70E+24	1.81E+25	1.24E+25	7.69E+24	0.315	0.525	2.352
Tianjin Emergy	1.000	3.364	0.753	3.29E+24	1.13E+25	8.00E+24	4.37E+24	0.292	0.518	2.584
Shanghai Emergy	1.000	2.152	1.161	1.07E+25	1.95E+25	8.76E+24	9.23E+24	0.550	0.474	2.111
Chongqing Emergy	1.000	35.223	0.260	3.23E+24	1.61E+25	1.29E+25	1.25E+25	0.201	0.465	1.293
Suzhou Material	0.129	1.747	0.639	7.84E+06	2.84E+07	2.05E+07	1.22E+07	0.277	0.513	2.312
Vienna Carbon	0	2.030	1.345	9.97E+03	2.43E+04	1.43E+04	4.97E+03	0.410	0.527	3.277
Stockholm Nitrogen	0.001	2.673	2.112	8.70E+04	1.61E+05	7.38E+04	3.08E+04	0.541	0.479	3.904
Stockholm Phosphorus	0.000	2.720	1.820	7.70E+03	1.41E+04	6.37E+03	3.09E+03	0.547	0.476	3.325
Beijing Nitrogen 1996	0.068	3.270	1.541	2.25E+03	6.48E+03	4.24E+03	1.07E+03	0.346	0.530	4.449
Beijing Nitrogen 2000	0.064	3.046	1.454	2.07E+03	6.65E+03	4.57E+03	1.03E+03	0.312	0.524	4.659
Beijing Nitrogen 2004	0.058	2.930	1.525	2.38E+03	7.33E+03	4.95E+03	1.11E+03	0.324	0.527	4.703
Beijing Nitrogen 2008	0.049	2.885	1.574	2.60E+03	7.58E+03	4.98E+03	1.20E+03	0.343	0.530	4.583
Beijing Nitrogen 2012	0.050	3.044	1.731	3.07E+03	8.04E+03	4.97E+03	1.33E+03	0.382	0.530	4.529
Gavle Phosphorus	0	2.270	1.995	2.10E+03	4.29E+03	2.19E+03	7.31E+02	0.489	0.505	4.079

Table 49 Flow-based ENA metrics for Food Webs

Network	FCI	MPL	AMI	ASC	DC	Φ	TST_P	Alpha	R	H
Mangroves (dry)	0.096	2.137	1.519	7.30E+03	2.20E+04	1.47E+04	3.27E+03	0.331	0.528	4.585
Mangroves (wet)	0.096	2.132	1.462	7.01E+03	2.20E+04	1.50E+04	3.27E+03	0.319	0.526	4.586
Middle Atlantic Bight	0.178	3.680	1.403	3.20E+04	1.15E+05	8.33E+04	1.79E+04	0.277	0.513	5.057
Southern New England Bight	0.161	3.730	1.406	3.14E+04	1.15E+05	8.36E+04	1.76E+04	0.273	0.511	5.152
Georges Bank	0.177	3.855	1.373	2.92E+04	1.10E+05	8.06E+04	1.69E+04	0.266	0.508	5.162
Gulf of Maine	0.150	3.637	1.397	3.27E+04	1.16E+05	8.29E+04	1.84E+04	0.283	0.515	4.936
Graminoids (dry)	0.037	2.165	1.905	2.09E+04	3.99E+04	1.89E+04	7.52E+03	0.526	0.488	3.626
Graminoids (wet)	0.018	2.181	1.937	3.86E+04	7.96E+04	4.09E+04	1.37E+04	0.486	0.506	3.989
Florida Bay (dry)	0.082	3.246	2.004	4.66E+03	1.23E+04	7.59E+03	1.78E+03	0.381	0.530	5.267
Florida Bay (wet)	0.144	3.684	2.025	7.00E+03	1.85E+04	1.15E+04	2.72E+03	0.378	0.531	5.359
Lake Oneida (pre-ZM)	0.000	1.613	1.257	3.36E+03	1.34E+04	1.00E+04	1.70E+03	0.251	0.501	5.010
Lake Oneida (post-ZM)	0.000	1.759	1.366	3.00E+03	1.13E+04	8.29E+03	1.49E+03	0.266	0.508	5.140
Bay of Quinte (pre-ZM)	0.004	1.748	1.513	4.70E+03	1.41E+04	9.38E+03	2.16E+03	0.334	0.528	4.534
Bay of Quinte (post-ZM)	0.001	1.499	1.156	2.83E+03	1.13E+04	8.48E+03	1.51E+03	0.250	0.500	4.622
Cypress (wet)	0.042	1.852	1.704	5.03E+03	1.47E+04	9.64E+03	1.92E+03	0.343	0.529	4.968
Cypress (dry)	0.044	1.812	1.649	6.58E+03	1.96E+04	1.30E+04	2.57E+03	0.335	0.529	4.918
Sylt-Romo Bight	0.118	4.360	1.850	3.90E+06	1.06E+07	6.65E+06	1.42E+06	0.370	0.531	5.005
Narragansett Bay	0.507	5.646	1.628	7.51E+06	2.05E+07	1.30E+07	3.92E+06	0.367	0.531	4.438
Neuse Estuary (late summer 1997)	0.126	2.810	1.952	3.45E+04	7.38E+04	3.93E+04	1.30E+04	0.468	0.513	4.173
Neuse Estuary (early summer 1998)	0.120	3.070	2.026	3.77E+04	8.01E+04	4.24E+04	1.40E+04	0.470	0.512	4.308
Neuse Estuary (early summer 1997)	0.116	3.153	2.075	3.78E+04	8.00E+04	4.22E+04	1.38E+04	0.472	0.511	4.391
St. Marks Seagrass, site 1 (Feb.)	0.113	2.644	1.844	4.04E+03	1.24E+04	8.40E+03	1.59E+03	0.325	0.527	5.676
St. Marks Seagrass, site 2 (Jan.)	0.088	2.294	1.827	3.63E+03	9.24E+03	5.61E+03	1.38E+03	0.393	0.530	4.651
Northern Benguela Upwelling	0.047	2.895	1.946	1.73E+04	3.59E+04	1.86E+04	6.61E+03	0.481	0.508	4.043
St. Marks Seagrass, site 4 (Feb.)	0.036	2.000	1.795	7.72E+03	1.90E+04	1.13E+04	2.87E+03	0.406	0.528	4.422
St. Marks Seagrass, site 1 (Jan.)	0.127	2.555	1.800	3.29E+03	9.85E+03	6.56E+03	1.32E+03	0.334	0.528	5.383
St. Marks Seagrass, site 2 (Feb.)	0.085	2.399	1.782	4.85E+03	1.46E+04	9.72E+03	1.92E+03	0.333	0.528	5.352
Neuse Estuary (late summer 1998)	0.112	2.665	1.924	3.98E+04	8.58E+04	4.60E+04	1.50E+04	0.464	0.514	4.151
St. Marks Seagrass, site 3 (Jan.)	0.007	1.620	1.563	3.20E+04	6.04E+04	2.84E+04	1.27E+04	0.529	0.486	2.953
Bothnian Sea	0.196	3.229	1.953	9.73E+02	2.06E+03	1.09E+03	4.26E+02	0.472	0.511	4.136
Bothnian Bay	0.066	2.151	1.635	2.16E+02	5.54E+02	3.38E+02	1.14E+02	0.389	0.530	4.198

Table 50 Strongly Connected Component results for UIEs

Network	Number of SCCs	Actors in SCCs	Percentage of Actors Involved in Cycling	Normalized Number of Actors in SCCs	Number of Actors per SCC
Central Arizona-Phoenix Nitrogen	1	8	80.00%	0.800	8
Central Arizona-Phoenix Nitrogen no Landfill	1	8	88.89%	0.889	8
Toronto Nitrogen 1990	1	2	33.33%	0.333	2
Toronto Nitrogen 2001	1	2	33.33%	0.333	2
Toronto Nitrogen 2004	1	2	33.33%	0.333	2
Swiss Lowlands Timber	1	2	33.33%	0.333	2
Swiss Lowlands Timber Scenario 1	1	2	33.33%	0.333	2
Swiss Lowlands Timber Scenario 2	2	4	66.67%	0.333	2
Central Arizona-Phoenix Wastewater Nitrogen	0	0	0.00%	0	0
Trinket Island Energy	0	0	0.00%	0	0
Xiamen Energy	2	6	85.71%	0.429	3
Beijing Energy 1995	1	2	50.00%	0.500	2
Beijing Energy 2000	1	3	75.00%	0.750	3
Beijing Energy 2005	0	0	0.00%	0.000	0
Beijing Energy 2007	1	3	75.00%	0.750	3
Beijing Emergy	1	3	100.00%	1.000	3
Tianjin Emergy	1	3	100.00%	1.000	3
Shanghai Emergy	1	3	100.00%	1.000	3
Chongqing Emergy	1	3	100.00%	1.000	3
Suzhou Material	1	14	93.33%	0.933	14
Vienna Carbon	0	0	0.00%	0	0
Stockholm Nitrogen	1	3	27.27%	0.273	3
Stockholm Phosphorus	0	0	0.00%	0	0
Beijing Nitrogen 1996	1	10	62.50%	0.625	10
Beijing Nitrogen 2000	1	10	62.50%	0.625	10
Beijing Nitrogen 2004	1	10	62.50%	0.625	10
Beijing Nitrogen 2008	1	10	62.50%	0.625	10
Beijing Nitrogen 2012	1	10	62.50%	0.625	10
Gavle Phosphorus	0	0	0.00%	0	0

Table 51 Strongly Connected Component results for Food Webs

Network	Number of SCCs	Actors in SCCs	Percentage of Actors Involved in Cycling	Normalized Number of Actors in SCCs	Number of Actors per SCC
Mangroves (dry)	1	85	90.43%	0.904	85
Mangroves (wet)	1	85	90.43%	0.904	85
Middle Atlantic Bight	1	30	93.75%	0.938	30
Southern New England Bight	1	31	93.94%	0.939	31
Georges Bank	1	29	93.55%	0.935	29
Gulf of Maine	1	29	93.55%	0.935	29
Graminoids (dry)	1	59	89.39%	0.894	59
Graminoids (wet)	1	59	89.39%	0.894	59
Florida Bay (dry)	1	102	81.60%	0.816	102
Florida Bay (wet)	1	102	81.60%	0.816	102
Lake Oneida (pre-ZM)	1	63	85.14%	0.851	63
Lake Oneida (post-ZM)	1	65	85.53%	0.855	65
Bay of Quinte (pre-ZM)	1	70	87.50%	0.875	70
Bay of Quinte (post-ZM)	1	64	86.49%	0.865	64
Cypress (wet)	1	52	76.47%	0.765	52
Cypress (dry)	1	52	76.47%	0.765	52
Sylt-Romo Bight	1	48	81.36%	0.814	48
Narragansett Bay	1	29	90.63%	0.906	29
Neuse Estuary (late summer 1997)	1	25	83.33%	0.833	25
Neuse Estuary (early summer 1998)	1	21	70.00%	0.700	21
Neuse Estuary (early summer 1997)	1	21	70.00%	0.700	21
St. Marks Seagrass, site 1 (Feb.)	1	29	56.86%	0.569	29
St. Marks Seagrass, site 2 (Jan.)	1	24	47.06%	0.471	24
Northern Benguela Upwelling	1	18	75.00%	0.750	18
St. Marks Seagrass, site 4 (Feb.)	1	27	52.94%	0.529	27
St. Marks Seagrass, site 1 (Jan.)	1	26	50.98%	0.510	26
St. Marks Seagrass, site 2 (Feb.)	1	26	50.98%	0.510	26
Neuse Estuary (late summer 1998)	1	22	73.33%	0.733	22
St. Marks Seagrass, site 3 (Jan.)	1	20	39.22%	0.392	20
Bothnian Sea	2	10	83.33%	0.417	5
Bothnian Bay	2	10	83.33%	0.417	5

Table 52 Strongly Connected Component results for EIPs

Network	Number of SCCs	Actors in SCCs	Percentage of Actors Involved in Cycling	Normalized Number of Actors in SCCs	Number of Actors per SCC
The Green Triangle	1	7	87.50%	0.875	7
Pomacle-Bazancourt	1	6	66.67%	0.667	6
Renova	1	11	100.00%	1.000	11
Clark Special Economic Zone	2	14	70.00%	0.350	7
Copper Industry Web	1	7	46.67%	0.467	7
Kytakyushu	1	7	63.64%	0.636	7
Kwinana	2	14	51.85%	0.259	7
Ulsan Industrial Park	2	9	56.25%	0.281	4.5
Humber ISP	1	6	35.29%	0.353	6
Uimaharju Forest Industry Park	1	8	88.89%	0.889	8
UPM Kymi pulp and paper mill	1	9	69.23%	0.692	9
Harjavalta Industrial Area	1	5	83.33%	0.833	5
GERIPA	1	6	75.00%	0.750	6
Kawasaki	1	8	100.00%	1.000	8
Kymi	1	6	75.00%	0.750	6
Burnside	2	7	63.64%	0.318	3.5
Devens	2	9	42.86%	0.214	4.5
Suzhou	1	7	77.78%	0.778	7
Guitang Sugarcane EIP Project	1	7	77.78%	0.778	7
Tianjin	1	6	75.00%	0.750	6
Guayama	1	4	66.67%	0.667	4
The Scotia Investments	1	5	71.43%	0.714	5
Kalundborg	1	3	21.43%	0.214	3
Seshasayee Paper and Board Ltd	1	6	85.71%	0.857	6
Mongstad	1	4	36.36%	0.364	4
An Son Village	1	4	100.00%	1.000	4
AES Thames	1	4	50.00%	0.500	4
Brownsville	2	5	31.25%	0.156	2.5
Barceloneta	1	3	42.86%	0.429	3
Red Hills EcoPlex	3	7	87.50%	0.292	2.333
Fushan Farms	1	4	57.14%	0.571	4
Nanning Sugar Company	2	6	75.00%	0.375	3
Monfort Boys Town	1	4	44.44%	0.444	4
Tunweni Brewery	1	6	75.00%	0.750	6
Lower Mississippi Corridor	2	4	17.39%	0.087	2
Stoneyfield Londonderry	1	2	15.38%	0.154	2

PV Symbiosis Prop	1	2	22.22%	0.222	2
Wallingford	1	2	16.67%	0.167	2
Styrian Recycling Network	3	6	15.38%	0.051	2
Landskrona	2	5	33.33%	0.167	2.5
Jyvaskyla	1	2	25.00%	0.250	2
NIA-KIADB	1	2	14.29%	0.143	2
Lubei Industrial Park	0	0	0	0	0
Gladstone 2008	0	0	0	0	0
Pingdingshan Coal Mining Group	0	0	0	0	0
Triangle J	0	0	0	0	0
Gladstone 2005	0	0	0	0	0
Connecticut Newsprint	0	0	0	0	0

Table 53 Centrality ranks for UIEs

Network		Betweenness		Degree		Closeness		Eigenvector	Average	
Central Arizona-Phoenix Nitrogen										
	1	Crops	1	Crops	1	Near-surface atmosphere	1	Crops	Crops	1.25
	2	Near-surface atmosphere	1	Near-surface atmosphere	2	Crops	2	Near-surface atmosphere	Near-surface atmosphere	1.5
	3	Urban landscapes	3	3 tied	2	Urban landscapes	3	Wastewater	Urban landscapes	3.75
									Wastewater	3.75
Central Arizona-Phoenix Nitrogen no Landfill										
	1	Crops	1	Crops	1	Near-surface atmosphere	1	Crops	Crops	1.25
	2	Near-surface atmosphere	1	Near-surface atmosphere	2	Crops	2	Near-surface atmosphere	Near-surface atmosphere	1.5
	3	Urban landscapes	3	Wastewater	3	Urban landscapes	3	Wastewater	Wastewater	3.5
Toronto Nitrogen 1990										
	1	Human Bodies	1	Human Bodies	1	Human Bodies	1	Human Bodies	Human Bodies	1
	2	All tied	2	All tied	2	All tied	2	Circular Outputs	Circular Outputs	2
							3	3 tied	3 tied	2.25
Swiss Lowlands Timber Baseline and Scenario 1										
	1	Production and trade of paper products	1	Incineration and waste management	1	Incineration and waste management	1	Incineration and waste management	Incineration and waste management	1.5

	2	Production and trade of timber products	2	Production and trade of timber products	2	Production and trade of timber products	2	Production and trade of timber products	Production and trade of timber products	2
	3	All tied	2	Production and trade of paper products	2	Production and trade of paper products	3	Production and trade of paper products	Production and trade of paper products	2
Swiss Lowlands Timber Scenario 2										
	1	Production and trade of timber products	1	Production and trade of timber products	1	Production and trade of timber products	1	Production and trade of paper products	Production and trade of paper products	1.25
	2	Production and trade of paper products	1	Production and trade of paper products	1	Production and trade of paper products	2	Incineration and waste management	Production and trade of timber products	1.5
	3	All tied	1	Incineration and waste management	1	Incineration and waste management	3	Production and trade of timber products	Incineration and waste management	1.75
Central Arizona-Phoenix Wastewater Nitrogen										
	1	All tied	1	Wastewater treatment plants	1	Wastewater treatment plants	1	Wastewater treatment plants	Wastewater treatment plants	1
			1	Groundwater	1	Groundwater	2	Groundwater	Groundwater	1.25
			3	Irrigated crops	3	Irrigated crops	3	Irrigated crops	Irrigated crops	2.5
			3	Biosolids	3	Biosolids				
Trinket Island Energy										
	1	Human Nutrition	1	Human Nutrition	1	Human Nutrition	1	Human Nutrition	Human Nutrition	1
	2	Electricity	2	Electricity	2	Electricity	2	Electricity	Electricity	2
	3	All tied	3	9 tied	3	3 tied	3	5 tied	4 tied	4.25
Xiamen Energy										

	1	Electric	1	Electric	1	Electric	1	Electric	Electric	1
	2	Industry	2	Industry	1	Industry	2	Industry	Industry	2
	2	Resident	3	Petrifaction	3	Petrifaction	3	Petrifaction	Petrifaction	3.25
Beijing Energy 1995										
	1	Energy Consumption sector	1	Energy Consumption sector	1	Energy Consumption sector	1	Energy Consumption sector	Energy Consumption sector	1
	2	All tied	2	Energy Exploitation sector	2	Energy Exploitation sector	2	Energy Exploitation sector	Energy Exploitation sector	2
			2	Energy Transformation sector	2	Energy Transformation sector	3	Energy Transformation sector	Energy Transformation sector	2.25
Beijing Energy 2000										
	1	Energy Consumption sector	1	Energy Consumption sector	1	Energy Consumption sector	1	Energy Consumption sector	Energy Consumption sector	1
	2	Energy Recovery sector	1	Energy Transformation sector	1	Energy Transformation sector	1	Energy Transformation sector	Energy Transformation sector	1.5
	3	Energy Exploitation sector	3	Energy Recovery sector	3	Energy Recovery sector	3	Energy Exploitation sector	Energy Recovery sector	3
	3	Energy Transformation sector	3	Energy Exploitation sector	3	Energy Exploitation sector			Energy Exploitation sector	3
Beijing Energy 2005										
	1	All tied	1	Energy Exploitation sector	1	Energy Exploitation sector	1	Energy Exploitation sector	Energy Exploitation sector	1
			1	Energy Transformation sector	1	Energy Transformation sector	1	Energy Consumption sector	Energy Recovery sector	1

			1	Energy Consumption sector	1	Energy Consumption sector	1	Energy Recovery sector	Energy Transformation sector	1.75
Beijing Energy 2007										
	1	Energy Transformation sector	1	Energy Transformation sector	1	Energy Transformation sector	1	Energy Transformation sector	Energy Transformation sector	1
	2	Energy Recovery sector	1	Energy Consumption sector	1	Energy Consumption sector	1	Energy Consumption sector	Energy Consumption sector	1.5
	3	Energy Consumption sector	3	Energy Exploitation sector	3	Energy Exploitation sector	3	Energy Exploitation sector	Energy Recovery sector	3
			3	Energy Recovery sector	3	Energy Recovery sector				
Chinese Cities Emergy										
	1	All tied	1	All tied	1	All tied	1	All tied	All tied	1
Suzhou Material										
	1	Construction	1	Other Manufacturing	1	Other Manufacturing	1	Other Manufacturing	Other Manufacturing	1.25
	2	Other Manufacturing	1	Production and Supply of Electric and Heat Power	1	Production and Supply of Electric and Heat Power	1	Production and Supply of Electric and Heat Power	Production and Supply of Electric and Heat Power	2
	3	Agriculture	3	3 tied	1	Construction	3	Textile	Chemistry	3.5
							3	Chemistry	Construction	3.5
Vienna Carbon										
	1	All tied	1	Agriculture sector	1	Agriculture sector	1	Domiestic sector	Domiestic sector	1
			1	Industry, trade,and service sector	1	Industry, trade,and service sector	2	Agriculture sector	Agriculture sector	1.25

			1	Domiestic sector	1	Domiestic sector	2	Industry, trade,and service sector	Industry, trade,and service sector	1.25
Stockholm Nitrogen										
	1	Air	1	Air	1	Air	1	Waste Management	Air	1.25
	2	Land	2	Waste Management	1	Waste Management	2	Air	Waste Management	1.75
	3	Service	3	Land	3	Land	3	Land	Land	2.75
	3	Waste Management	3	Service	3	Real Estate				
Stockholm Phosphorus										
	1	Service	1	Service	1	Service	1	Waste Management	Service	1.25
	2	Waste Management	1	Waste Management	1	Waste Management	2	Service	Waste Management	1.25
	3	Land	3	Land	3	3 tied	3	Land	Land	3
	3	Real Estate								
Beijing Nitrogen										
	1	Atmosphere	1	Atmosphere	1	Atmosphere	1	Atmosphere	Atmosphere	1
	2	Crop Cultivation	2	Industry	2	Industry	2	Industry	Household	3.5
	3	Household	3	Surface water	3	Surface water	3	Household	Industry	4
									Surface water	4
Gavle Phosphorus										
	1	Population Centre	1	Population Centre	1	Population Centre	1	Population Centre	Population Centre	1
	2	Forests and Agriculture	2	Waste Dumps	2	Waste Dumps	2	Waste Dumps	Waste Dumps	2.25
	3	All tied	3	Forests and Agriculture	3	Forests and Agriculture	3	Forests and Agriculture	Forests and Agriculture	2.75

Table 54 Centrality ranks for Food Webs

Network		Betweenness		Degree		Closeness		Eigenvector	Average	
Bothnian Bay										
	1	Sedimentary Carbon	1	Sedimentary Carbon	1	Sedimentary Carbon	1	Sedimentary Carbon	Sedimentary Carbon	1
	2	Dissolved organic matter	2	Mesozooplankton	2	Mesozooplankton	2	Mesozooplankton	Mesozooplankton	2.25
	3	Mesozooplankton	2	Dissolved organic matter	2	Dissolved organic matter	3	Demersal Fish	Dissolved organic matter	2.5
			2	Demersal Fish						
Bothnian Sea										
	1	Sedimentary Carbon	1	Sedimentary Carbon	1	Sedimentary Carbon	1	Sedimentary Carbon	Sedimentary Carbon	1
	2	Dissolved Organic Matter	2	Mesozooplankton	2	Mesozooplankton	2	Mesozooplankton	Mesozooplankton	2.25
	3	Mesozooplankton	2	Demersal Fish	2	Dissolved organic matter	3	Demersal Fish	Dissolved organic matter	3
	3	Microzooplankton	2	Macrofauna						
			2	Dissolved Organic Matter						
Georges Bank										

	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	Detritus - Particulate Organic Carbon	1
	2	Discards	2	Macrobenthos- molluscs	2	Macrobenthos- molluscs	2	Sharks- pelagics	Macrobenthos- molluscs	2.5
	3	Macrobenthos- molluscs	2	Sharks- pelagics	2	Sharks- pelagics	3	Macrobenthos- molluscs	Sharks- pelagics	3.25
Gulf of Maine										
	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	Detritus - Particulate Organic Carbon	1
	2	Discards	2	Macrobenthos- crustacea	2	Macrobenthos- crustacea	2	Macrobenthos- crustacea	Macrobenthos- crustacea	2.25
	3	Macrobenthos- molluscs	3	Macrobenthos- other	3	Small Pelagics- commer	3	Demersals- piscivores	Macrobenthos- other	4
			3	Demersals- omnivores	3	Discards				
			3	Demersals- piscivores						
Lake Oneida (post-ZM)										
	1	Pelagic Detritus	1	Insects	1	Insects	1	Insects	Insects	2.25
	2	Sedimented Detritus	2	Leeches	2	Leeches	2	Leeches	Leeches	3.75
	3	White Perch Age 1+	3	Walleye Age 0	3	Walleye Age 0	3	Walleye Age 0	Walleye Age 0	5
					3	Sedimented Detritus				

					3	Gizzard Shad Age 0				
					3	Yellow Perch Age 3+				
Lake Oneida (pre-ZM)										
	1	Pelagic Detritus	1	Insects	1	Insects	1	Insects	Insects	2.25
	2	White Perch Age 1+	2	Leeches	2	Leeches	2	Leeches	Leeches	3.5
	3	Sedimented Detritus	3	Walleye Age 0	3	Sedimented Detritus	3	Walleye Age 0	Sedimented Detritus	5
Bay of Quinte (post-ZM)										
	1	Sedimented Detritus	1	Yellow Perch Age 1+	1	Yellow Perch Age 1+	1	Yellow Perch Age 1+	Walleye Age 0	3
	2	Pelagic Detritus	2	Insects	2	Insects	2	Walleye Age 0	Sedimented Detritus	3
	3	Harpacticoida	3	Walleye Age 0	3	Walleye Age 0	3	Insects	Insects	3.5
					3	Sedimented Detritus				
Bay of Quinte (pre-ZM)										
	1	Sedimented Detritus	1	Insects	1	Insects	1	Yellow Perch Age 1+	Insects	2.75
	2	Pelagic Detritus	2	Yellow Perch Age 1+	1	Yellow Perch Age 1+	2	Walleye Age 0	Walleye Age 0	3.25
	3	Pumpkinseed Age 1+	3	Walleye Age 0	3	Walleye Age 0	3	Insects	Pumpkinseed Age 1+	5

Middle Atlantic Bight										
	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	Detritus - Particulate Organic Carbon	1
	2	Discards	2	Small Pelagics- commer	2	Discards	2	Small Pelagics- commer	Macrobenthos- crustacea	2.5
	3	Macrobenthos- crustacea	2	Macrobenthos- crustacea	2	Small Pelagics- commer	3	Macrobenthos- crustacea	Small Pelagics- commer	3.25
					2	Macrobenthos- crustacea				
Southern New England Bight										
	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	1	Detritus - Particulate Organic Carbon	Detritus - Particulate Organic Carbon	1
	2	Discards	2	Discards	2	Discards	2	Demersals- piscivores	Discards	2.75
	3	Macrobenthos- crustacea	2	Macrobenthos- crustacea	3	Small Pelagics- commer	3	Small Pelagics- commer	Macrobenthos- crustacea	3.25
			2	Demersals- piscivores						
Sylt-Romo Bight										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1

	2	Corophium arenarium	2	Sediment bacteria	2	Crangon	2	Sediment bacteria	Crangon	3
	3	Suspended Particulate Organic Carbon	2	Crangon	2	Nereis diversicolor	3	Crangon	Nereis diversicolor	4.25
Cypress (dry)										
	1	Vertebrate Det.	1	Vertebrate Det.	1	Vertebrate Det.	1	Vertebrate Det.	Vertebrate Det.	1
	2	Ter. Invertebrates	2	Ter. Invertebrates	2	Ter. Invertebrates	2	Ter. Invertebrates	Ter. Invertebrates	2
	3	Liable Det.	3	Small Fish, prim. Carniv	3	Small Fish, prim. Carniv	3	Snakes	Snakes	3.5
			3	Snakes	3	Snakes				
Cypress (wet)										
	1	Vertebrate Det.	1	Vertebrate Det.	1	Vertebrate Det.	1	Vertebrate Det.	Vertebrate Det.	1
	2	Ter. Invertebrates	2	Ter. Invertebrates	2	Ter. Invertebrates	2	Ter. Invertebrates	Ter. Invertebrates	2
	3	Liable Det.	3	Snakes	3	Snakes	3	Snakes	Snakes	3.5
Florida Bay (dry)										
	1	Water Particulate Organic Carbon	1	Water Particulate Organic Carbon	1	Water Particulate Organic Carbon	1	Water Particulate Organic Carbon	Water Particulate Organic Carbon	1
	2	Benthic Particulate Organic Carbon	2	Predatory Shrimp	2	Predatory Shrimp	2	Predatory Shrimp	Predatory Shrimp	4.25
	3	Bivalves	3	Pink Shrimp	3	Pink Shrimp	3	Pink Shrimp	Pink Shrimp	4.5

Florida Bay (wet)										
	1	Water Particulate Organic Carbon	1	Water Particulate Organic Carbon	1	Water Particulate Organic Carbon	1	Water Particulate Organic Carbon	Water Particulate Organic Carbon	1
	2	Benthic Particulate Organic Carbon	2	Predatory Shrimp	2	Predatory Shrimp	2	Predatory Shrimp	Predatory Shrimp	4.25
	3	Bivalves	3	Pink Shrimp	3	Pink Shrimp	3	Pink Shrimp	Pink Shrimp	4.5
Graminoids (dry)										
	1	Refractory Detritus	1	Refractory Detritus	1	Refractory Detritus	1	Refractory Detritus	Refractory Detritus	1
	2	Sediment Carbon	2	Sediment Carbon	2	Sediment Carbon	2	Sediment Carbon	Sediment Carbon	2
	3	Mesoinverts	3	Mesoinverts	3	Mesoinverts	3	Mesoinverts	Mesoinverts	3
Graminoids (wet)										
	1	Refractory Detritus	1	Refractory Detritus	1	Refractory Detritus	1	Refractory Detritus	Refractory Detritus	1
	2	Sediment Carbon	2	Sediment Carbon	2	Sediment Carbon	2	Sediment Carbon	Sediment Carbon	2
	3	Mesoinverts	3	Mesoinverts	3	Mesoinverts	3	Mesoinverts	Mesoinverts	3
Mangroves (dry)										
	1	Carbon in Sediment	1	Carbon in Sediment	1	Carbon in Sediment	1	Particulate Organic Carbon	Carbon in Sediment	1.25

	2	Particulate Organic Carbon	2	Particulate Organic Carbon	2	Particulate Organic Carbon	2	Carbon in Sediment	Particulate Organic Carbon	1.75
	3	Insect	3	Snakes	3	Snakes	3	Snakes	Snakes	3.5
Mangroves (wet)										
	1	Carbon in Sediment	1	Carbon in Sediment	1	Carbon in Sediment	1	Particulate Organic Carbon	Carbon in Sediment	1.25
	2	Particulate Organic Carbon	2	Particulate Organic Carbon	2	Particulate Organic Carbon	2	Carbon in Sediment	Particulate Organic Carbon	1.75
	3	Insect	3	Snakes	3	Snakes	3	Snakes	Snakes	4.5
Narragansett Bay										
	1	Detritus	1	Detritus	1	Detritus	1	Detritus	Detritus	1
	2	Mesozooplankton	2	Mesozooplankton	2	Shrimp(Pal,Crg)	2	Ben Macrofauna	Shrimp(Pal,Crg)	2.5
	3	Shrimp(Pal,Crg)	2	Shrimp(Pal,Crg)	2	Ben Macrofauna	3	Shrimp(Pal,Crg)	Ben Macrofauna	2.75
			2	Ben Macrofauna						
Northern Benguela Upwelling										
	1	Microplankton	1	Particulate Organic Carbon	1	Particulate Organic Carbon	1	Particulate Organic Carbon	Particulate Organic Carbon	1.25

	2	Particulate Organic Carbon	2	Hake	2	Hake	2	Hake	Hake	3.5
	3	Mesozooplankton	3	Carnivorous Fish	3	Carnivorous Fish	3	Carnivorous Fish	Macrozooplankton	4.5
					3	Macrozooplankton				
Neuse Estuary (early summer 1997)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Sediment bacteria	2	Meiobenthos	2	Meiobenthos	2	Meiobenthos	Meiobenthos	3.25
	3	DOC	3	Deposit feeding polychaet	2	Suspension feeding mollus	3	Deposit feeding polychaet	Deposit feeding polychaet	4.5
			3	Pelagic-demersal fish						
Neuse Estuary (early summer 1998)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Sediment bacteria	2	Demersal fish	2	Demersal fish	2	Meiobenthos	Sediment bacteria	4.5
	3	DOC	3	Meiobenthos	2	Suspended Particulate Organic Carbon	3	Demersal fish	Demersal fish	4.75

					2	Suspension feeding mollus			Meiobenthos	4.75
Neuse Estuary (late summer 1997)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Suspended Particulate Organic Carbon	2	Meiobenthos	2	Meiobenthos	2	Meiobenthos	Meiobenthos	2.5
	3	Sediment bacteria	3	Deposit feeding polychaet	3	Suspended Particulate Organic Carbon	3	Deposit feeding polychaet	Sediment bacteria	4.25
					3	Other susp. feed. Mollusk				
Neuse Estuary (late summer 1998)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Suspended Particulate Organic Carbon	2	Meiobenthos	2	Meiobenthos	2	Meiobenthos	Meiobenthos	2.5
	3	Sediment bacteria	3	Demersal fish	3	Demersal fish	3	Demersal fish	Sediment bacteria	5
					3	Suspended Particulate Organic Carbon				
					3	Other susp. feed. Mollusk				

St. Marks Seagrass, site 1 (Feb.)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Benthic bacteria	2	Predatory polycht	2	Predatory polycht	2	Predatory polycht	Predatory polycht	3.5
	3	Epiphyte-graz amphipods	3	Omnivorous crabs	3	Omnivorous crabs	3	Omnivorous crabs	Omnivorous crabs	4.75
St. Marks Seagrass, site 2 (Feb.)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Benthic bacteria	2	Predatory polycht	2	Predatory polycht	2	Predatory polycht	Predatory polycht	4.5
	3	Epiphyte-graz amphipods	3	Predatory shrimp	2	Spot	3	Predatory shrimp	Benthic bacteria	6.5
			3	Omnivorous crabs						
			3	Benthic algae						
St. Marks Seagrass, site 4 (Feb.)										

	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Benthic bacteria	2	Predatory polycht	2	Predatory polycht	2	Predatory polycht	Predatory polycht	4.5
	3	Epiphyte-graz amphipods	3	Benthic algae	3	Epiphyte-graz amphipods	3	Benthic bacteria	Benthic bacteria	4.5
					3	Benthic algae				
St. Marks Seagrass, site 1 (Jan.)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Benthic bacteria	2	Predatory shrimp	2	Predatory shrimp	2	Meiofauna	Benthic bacteria	3.75
	3	Epiphyte-graz amphipods	3	Meiofauna	3	Benthic algae	3	Benthic bacteria	Predatory shrimp	4.25
St. Marks Seagrass, site 2 (Jan.)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Benthic bacteria	2	Predatory shrimp	2	Predatory shrimp	2	Predatory shrimp	Benthic bacteria	3.5

	3	Epiphyte-graz amphipods	3	Benthic bacteria	3	Sheepshead minnow	3	Benthic bacteria	Predatory shrimp	3.5
St. Marks Seagrass, site 3 (Jan.)										
	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	1	Sediment Particulate Organic Carbon	Sediment Particulate Organic Carbon	1
	2	Benthic bacteria	2	Benthic bacteria	2	Epiphyte-graz amphipods	2	Benthic bacteria	Benthic bacteria	2.75
	3	Suspended Particulate Organic Carbon	2	Epiphyte-graz amphipods	3	Benthic algae	3	Meiofauna	Epiphyte-graz amphipods	3
			2	Meiofauna	3	Sheepshead minnow				

Table 55 Utility Analysis results and Mutualism Index for UIEs

Network	Exploit	Mutualism	Competition	Neutral	Mutualism Index
Central Arizona-Phoenix Nitrogen	53.33%	17.78%	28.89%	0.00%	1.000
Central Arizona-Phoenix Nitrogen no Landfill	58.33%	16.67%	25.00%	0.00%	1.077
Toronto Nitrogen 1990	26.67%	0.00%	40.00%	33.33%	0.625
Toronto Nitrogen 2001	26.67%	0.00%	40.00%	33.33%	0.625
Toronto Nitrogen 2004	26.67%	0.00%	40.00%	33.33%	0.625
Swiss Lowlands Timber	60.00%	13.33%	26.67%	0.00%	1.118
Swiss Lowlands Timber Scenario 1	60.00%	13.33%	26.67%	0.00%	1.118
Swiss Lowlands Timber Scenario 2	73.33%	13.33%	13.33%	0.00%	1.400
Central Arizona-Phoenix Wastewater Nitrogen	53.33%	13.33%	33.33%	0.00%	1.000
Trinket Island Energy	7.58%	4.55%	1.52%	86.36%	1.250
Xiamen Energy	57.14%	9.52%	33.33%	0.00%	0.885
Beijing Energy 1995	33.33%	16.67%	0.00%	50.00%	4.000
Beijing Energy 2000	66.67%	16.67%	16.67%	0.00%	1.667
Beijing Energy 2005	33.33%	16.67%	0.00%	50.00%	2.200
Beijing Energy 2007	66.67%	16.67%	16.67%	0.00%	1.667
Beijing Emergy	100.00%	0.00%	0.00%	0.00%	2.000
Tianjin Emergy	66.67%	0.00%	33.33%	0.00%	1.250
Shanghai Emergy	66.67%	0.00%	33.33%	0.00%	1.250
Chongqing Emergy	66.67%	0.00%	33.33%	0.00%	1.250
Suzhou Material	43.81%	7.62%	48.57%	0.00%	0.520
Vienna Carbon	66.67%	0.00%	33.33%	0.00%	0.800
Stockholm Nitrogen	38.18%	16.36%	10.91%	34.55%	1.244
Stockholm Phosphorus	42.86%	28.57%	3.57%	25.00%	2.048
Beijing Nitrogen 1996	49.17%	13.33%	37.50%	0.00%	0.718
Beijing Nitrogen 2000	42.50%	14.17%	43.33%	0.00%	0.652
Beijing Nitrogen 2004	45.83%	13.33%	40.83%	0.00%	0.673
Beijing Nitrogen 2008	54.17%	15.00%	30.83%	0.00%	0.842
Beijing Nitrogen 2012	54.17%	16.67%	29.17%	0.00%	0.896
Gavle Phosphorus	51.11%	20.00%	28.89%	0.00%	1.041

Table 56 Utility Analysis results and Mutualism Index for Food Webs

Network	Exploit	Mutualism	Competition	Neutral	Mutualism Index
Mangroves (dry)	48.73%	21.37%	29.90%	0.00%	0.863
Mangroves (wet)	47.86%	21.55%	30.59%	0.00%	0.854
Middle Atlantic Bight	53.43%	25.20%	21.37%	0.00%	1.147
Southern New England Bight	51.33%	26.70%	21.97%	0.00%	1.165
Georges Bank	53.55%	24.73%	21.72%	0.00%	1.131
Gulf of Maine	52.47%	23.66%	23.87%	0.00%	1.062
Graminoids (dry)	46.34%	14.13%	39.53%	0.00%	0.619
Graminoids (wet)	47.41%	13.01%	39.58%	0.00%	0.604
Florida Bay (dry)	47.86%	19.74%	32.40%	0.00%	0.790
Florida Bay (wet)	47.75%	20.39%	31.86%	0.00%	0.809
Lake Oneida (pre-ZM)	51.43%	20.29%	28.29%	0.00%	0.877
Lake Oneida (post-ZM)	51.33%	23.47%	25.19%	0.00%	0.992
Bay of Quinte (pre-ZM)	51.08%	14.94%	33.99%	0.00%	0.701
Bay of Quinte (post-ZM)	51.20%	15.92%	32.88%	0.00%	0.733
Cypress (wet)	42.63%	18.53%	38.85%	0.00%	0.687
Cypress (dry)	45.83%	16.37%	37.80%	0.00%	0.672
Sylt-Romo Bight	50.50%	15.84%	30.27%	3.39%	0.780
Narragansett Bay	44.15%	30.24%	25.60%	0.00%	1.165
Neuse Estuary (late summer 1997)	44.60%	19.31%	22.99%	13.10%	0.996
Neuse Estuary (early summer 1998)	31.49%	15.17%	16.78%	36.55%	1.036
Neuse Estuary (early summer 1997)	33.33%	15.40%	14.71%	36.55%	1.083
St. Marks Seagrass, site 1 (Feb.)	42.20%	13.80%	25.18%	18.82%	0.832
St. Marks Seagrass, site 2 (Jan.)	32.55%	9.57%	19.06%	38.82%	0.863
Northern Benguela Upwelling	49.28%	12.32%	38.41%	0.00%	0.655
St. Marks Seagrass, site 4 (Feb.)	43.69%	15.76%	21.73%	18.82%	0.925
St. Marks Seagrass, site 1 (Jan.)	38.82%	11.14%	20.86%	29.18%	0.859
St. Marks Seagrass, site 2 (Feb.)	42.51%	15.45%	23.22%	18.82%	0.893
Neuse Estuary (late summer 1998)	35.40%	16.32%	17.24%	31.03%	1.050
St. Marks Seagrass, site 3 (Jan.)	19.06%	7.80%	12.00%	61.14%	0.959
Bothnian Sea	0.5303	0.2576	0.2121	0	1.286
Bothnian Bay	54.55%	22.73%	22.73%	0.00%	1.182

Table 57 Top ranked actors based on positive and negative Utility for UIEs

Network	Positive Utility	Negative Utility

Central Arizona-Phoenix Nitrogen				
	1	Crops	1	Near-surface atmosphere
	2	3 tied	2	3 tied
Central Arizona-Phoenix Nitrogen no Landfill				
	1	Crops	1	Near-surface atmosphere
	1	Wastewater	2	3 tied
Toronto Nitrogen 1990				
	1	Human Bodies	1	4 tied
Toronto Nitrogen 2001				
	1	Human Bodies	1	4 tied
Toronto Nitrogen 2004				
	1	Human Bodies	1	4 tied
Swiss Lowlands Timber				
	1	Forestry	1	Incineration and waste management
			2	4 tied
Swiss Lowlands Timber Scenario 1				
	1	Forestry	1	Incineration and waste management
			2	4 tied
Swiss Lowlands Timber Scenario 2				
	1	Forestry	1	Incineration and waste management
	1	Consumption of paper products	2	Production and trade of paper products
			2	Consumption of timber products
Central Arizona-Phoenix Wastewater Nitrogen				
	1	Wastewater treatment plants	1	Irrigated crops
	2	Septic tanks	1	Palo Verde Power Plant
			1	Biosolids
Trinket Island Energy				
	1	Solar Panels	1	Human Nutrition
	2	5 tied	1	Mechanical Energy
			1	Process Energy
Xiamen Energy				
	1	N/A	1	Industry
			2	3 tied

Beijing Energy 1995				
	1	Energy Exploitation sector	1	N/A
Beijing Energy 2000				
	1	Energy Exploitation sector	1	Energy Transformation sector
	1	Energy Consumption sector	1	Energy Recovery sector
Beijing Energy 2005				
	1	Energy Exploitation sector	1	N/A
Beijing Energy 2007				
	1	Energy Exploitation sector	1	Energy Transformation sector
	1	Energy Consumption sector	1	Energy Recovery sector
Beijing Emergy				
	1	Domestic Sector	1	Industrial Sector
Tianjin Emergy				
	1	Domestic Sector	1	Industrial Sector
			1	Agricultural Sector
Shanghai Emergy				
	1	Domestic Sector	1	Industrial Sector
			1	Agricultural Sector
Chongqing Emergy				
	1	Domestic Sector	1	Industrial Sector
			1	Agricultural Sector
Suzhou Material				
	1	Mining	1	Chemistry
			2	3 tied
Vienna Carbon				
	1	Energy production sector	1	Industry, trade, and service sector
	1	Water and soil	1	Domestic sector
	1	Construction sector	2	Agriculture sector
Stockholm Nitrogen				
	1	Food Supply	1	Air
	2	Service	2	Transport
			2	Infrastructure
Stockholm Phosphorus				
	1	Food Supply	1	N/A
	2	Service		
Beijing Nitrogen 1996				

	1	Industry	1	Aquaculture
	2	Forest	2	5 tied
Beijing Nitrogen 2000				
	1	Industry	1	Forestry
	2	Forest	1	Service
			1	Construction
			1	Transportation
Beijing Nitrogen 2004				
	1	Industry	1	Aquaculture
	2	Forest	2	5 tied
Beijing Nitrogen 2008				
	1	Industry	1	Aquaculture
	2	Sewage treatment	2	Transportation
Beijing Nitrogen 2012				
	1	Industry	1	Pets
	1	Sewage treatment	1	Atmosphere
Gavle Phosphorus				
	1	Rivers	1	Waste Dumps
	1	Poultry	1	7 tied

Table 58 Top ranked actors based on positive and negative Utility for Food Webs

Network		**Positive Utility**		**Negative Utility**
Bothnian Bay				
	1	Pelagic Producers	1	Sedimentary Carbon
	1	Meiofauna	1	Dissolved Organic Matter
Bothnian Sea				
	1	Pelagic Producers	1	Dissolved Organic Matter
	2	Meiofauna	2	Sedimentary Carbon
Georges Bank				
	1	Phytoplankton- Primary	1	Megabenthos- filterers
	2	Bacteria	2	Megabenthos- other
	2	Large Copepods		
	2	Micronekton		
Gulf of Maine				
	1	Phytoplankton- Primary	1	Gelatinous Zooplankton
	2	Micronekton	1	Megabenthos- filterers
			1	Demersals- piscivores

			1	Odontocetes
Lake Oneida (post-ZM)				
	1	Euglena	1	Yellow Perch Age 3+
	1	Flagellates	1	Gizzard Shad Age 0
	1	Golden Algae		
	1	Green Algae		
Lake Oneida (pre-ZM)				
	1	Diatoms	1	Dissolved Organic Carbon
	2	Golden Algae	2	Pelagic Detritus
Bay of Quinte (post-ZM)				
	1	Diatoms	1	Eucyclops species
	2	Flagellates	2	Cyclopoida copepodites
	2	Golden Algae	2	Ceriodaphnia species
Bay of Quinte (pre-ZM)				
	1	Golden Algae	1	Dissolved Organic Carbon
	2	Diatoms	2	Pelagic Detritus
Middle Atlantic Bight				
	1	Phytoplankton- Primary	1	Baleen Whales
	2	Large Copepods	2	Gelatinous Zooplankton
			2	Demersals- piscivores
			2	Sea Birds
Southern New England Bight				
	1	Phytoplankton- Primary	1	Baleen Whales
	2	Bacteria	1	Detritus- Particulate Organic Carbon
Sylt-Romo Bight				
	1	Sediment bacteria	1	Capitellidae
	2	Kabeljauw (G. morhua)	1	Gammarus spp.
	2	Bull Rout (M. scorpius)	1	Tharyx killariensis
Cypress (dry)				
	1	Terrestrial Invertebrates	1	Refractory Detritus
	2	Vine Leaves	2	Floating Vegetation
	2	HW Wood		
	2	Roots		
Cypress (wet)				
	1	Living SED	1	Refractory Detritus
	2	Terrestrial Invertebrates	2	Floating Vegetation
	2	Vultures		
Florida Bay (dry)				
	1	Benthic Phytoplankton	1	Water Cilitaes

	2	Synedococcus	2	Paracalanus
Florida Bay (wet)				
	1	Synedococcus	1	Water Cilitaes
	2	Benthic Phytoplankton	2	Drift Algae
Graminoids (dry)				
	1	Sediment Carbon	1	Refractory Detritus
	2	Labile Detritus	2	Gruiformes
Graminoids (wet)				
	1	Sediment Carbon	1	Refractory Detritus
	2	Living Particulate Organic Carbon	2	Gruiformes
	2	Panthers		
Mangroves (dry)				
	1	Other Phytoplankton	1	Manatee
	2	Phytoplankton	2	Racoon
	2	MICR. H2O		
Mangroves (wet)				
	1	Other Phytoplankton	1	Manatee
	2	MICR. H2O	2	Squirrel
Narragansett Bay				
	1	Phytoplankton	1	Detritus
	2	Sediment Particulate Organic Carbon Bacteria	2	Hard Clam
Northern Benguela Upwelling				
	1	Phytoplankton	1	Particulate Organic Carbon
	2	Microplankton	2	Rock Lobster
Neuse Estuary (early summer 1997)				
	1	Phytoplankton	1	Isopods
	1	Free living bacteria	2	Deposit feeding amphipods
	1	Suspension feeding mollus		
	1	Sediment bacteria		
Neuse Estuary (early summer 1998)				
	1	Benthic microalgae	1	Isopods
	2	Free living bacteria	2	Depost feed. gastropods
Neuse Estuary (late summer 1997)				
	1	Free living bacteria	1	Isopods
	2	Sediment bacteria	2	Brown & Pink shrimp
Neuse Estuary (late summer 1998)				

	1	Free living bacteria	1	Predatory polychaetes
	2	Sediment bacteria	2	Oyster
St. Marks Seagrass, site 1 (Feb.)				
	1	Benthic bacteria	1	Dissolved Organic Carbon
	2	Raptors	2	Detritus feed crust.
St. Marks Seagrass, site 2 (Feb.)				
	1	Benthic bacteria	1	Dissolved Organic Carbon
	2	Blue crab	2	Micro protozoa
St. Marks Seagrass, site 4 (Feb.)				
	1	Bacterio plankton	1	Omnivorous crabs
	2	Benthos-eating birds	1	Deposit-feed gastropods
St. Marks Seagrass, site 1 (Jan.)				
	1	Bacterio-plankton	1	Detritus feed crustacea
	2	Benthic bacteria	1	Omnivorous crabs
St. Marks Seagrass, site 2 (Jan.)				
	1	bacterio-plankton	1	Dissolved Organic Carbon
	2	benthic bacteria	2	brittle stars
St. Marks Seagrass, site 3 (Jan.)				
	1	epiphyte graz amphipods	1	Dissolved Organic Carbon
	1	benthic bacteria	2	brittle stars

Table 59 Mixed Trophic Impact results for UIEs

Network	Largest cumulative absolute impact	Largest cumulative positive	Largest cumulative negative
Central Arizona-Phoenix Nitrogen	Near-Surface Atmosphere	Humans	Near-Surface Atmosphere
Central Arizona-Phoenix Nitrogen no Landfill	Near-Surface Atmosphere	Dairies	Near-Surface Atmosphere
Toronto Nitrogen 1990	Human Bodies	Human Bodies	Incineration
Toronto Nitrogen 2001	Human Bodies	Human Bodies	Atmospheric Release

Toronto Nitrogen 2004	Human Bodies	Human Bodies	Atmospheric Release
Swiss Lowlands Timber	Incineration	Forestry	Incineration and Waste Management
Swiss Lowlands Timber Scenario 1	Incineration	Forestry	Incineration and Waste Management
Swiss Lowlands Timber Scenario 2	Production and trade of timber products	Forestry	Incineration and Waste Management
Central Arizona-Phoenix Wastewater Nitrogen	Wastewater treatment plants	Wastewater treatment plants	Groundwater
Trinket Island Energy	Human Nutrition	Solar Panels	Human Nutrition, Mechanical Energy, and Process Energy
Xiamen Energy	Industry	Petrifaction	Industry
Beijing Energy 1995	Energy Transformation Sector	Energy Exploitation Sector	Energy Transformation Sector
Beijing Energy 2000	Energy Consumption Sector	Energy Exploitation Sector	Energy Transformation Sector
Beijing Energy 2005	Energy Consumption Sector	Energy Exploitation Sector	Energy Transformation Sector
Beijing Energy 2007	Energy Consumption Sector	Energy Consumption Sector	Energy Transformation Sector
Beijing Emergy	Industrial Sector	Domestic Sector	Industrial Sector
Tianjin Emergy	Industrial Sector	Domestic Sector	Industrial Sector
Shanghai Emergy	Industrial Sector	Domestic Sector	Industrial Sector
Chongqing Emergy	Agricultural Sector	Domestic Sector	Agricultural Sector
Suzhou Material	Agriculture	Mining	Services
Vienna Carbon	Domestic Sector	Water and Soil	Domestic Sector
Stockholm Nitrogen	Air	Food Supply	Air
Stockholm Phosphorus	Service	Food Supply	Land
Beijing Nitrogen 1996	Atmosphere	Industry	Atmosphere
Beijing Nitrogen 2000	Atmosphere	Industry	Atmosphere
Beijing Nitrogen 2004	Atmosphere	Industry	Atmosphere
Beijing Nitrogen 2008	Atmosphere	Industry	Atmosphere
Beijing Nitrogen 2012	Atmosphere	Industry	Transportation
Gavle Phosphorus	Population Centre	Poultry	Waste Dumps

Table 60 Mixed Trophic Impact results for Food Webs

Network	**Largest cumulative absolute impact**	**Largest cumulative positive**	**Largest cumulative negative**
Mangroves (dry)	POC	Oth. PP	POC
Mangroves (wet)	POC	Oth. PP	POC
Middle Atlantic Bight	Detritus - POC	Phytoplankton - Primary	Gelatinous Zooplankton
Southern New England Bight	Detritus - POC	Phytoplankton - Primary	Detritus - POC
Georges Bank	Detritus - POC	Phytoplankton - Primary	Gelatinous Zooplankton
Gulf of Maine	Detritus - POC	Phytoplankton - Primary	Gelatinous Zooplankton

Graminoids (dry)	Refractory Detritus	Sediment Carbon	Refractory Detritus
Graminoids (wet)	Refractory Detritus	Sediment Carbon	Refractory Detritus
Florida Bay (dry)	Water POC	Epiphytes	Water POC
Florida Bay (wet)	Water POC	Water Flagellates	Water POC
Lake Oneida (pre-ZM)	Sedimented Detritus	Golden Algae	Pelagic Detritus
Lake Oneida (post-ZM)	Sedimented Detritus	Diatoms	Pelagic Detritus
Bay of Quinte (pre-ZM)	Sedimented Detritus	Diatoms	Sedimented Detritus
Bay of Quinte (post-ZM)	Sedimented Detritus	Green Algae	Sedimented Detritus
Cypress (wet)	Vertebrate Detritus	Terrestrial Invertebrates	Vertebrate Detritus
Cypress (dry)	Vertebrate Detritus	Terrestrial Invertebrates	Vertebrate Detritus
Sylt-Romo Bight	Sediment POC	Sediment Bacteria	Sediment POC
Narragansett Bay	Detritus	Phytoplankton	Detritus
Neuse Estuary (late summer 1998)	Sediment POC	Sediment Bacteria	Sediment POC
Neuse Estuary (early summer 1998)	Sediment POC	Sediment Bacteria	Sediment POC
Neuse Estuary (early summer 1997)	Sediment POC	Sediment Bacteria	Sediment POC
St. Marks Seagrass, site 1 (Feb.)	Sediment POC	Benthic Bacteria	Sediment POC
St. Marks Seagrass, site 2 (Jan.)	Sediment POC	Benthic Bacteria	Sediment POC
Northern Benguela Upwelling	POC	Phytoplankton	POC
St. Marks Seagrass, site 4 (Feb.)	Sediment POC	Benthic Bacteria	Sediment POC
St. Marks Seagrass, site 1 (Jan.)	Sediment POC	Benthic Bacteria	Sediment POC
St. Marks Seagrass, site 2 (Feb.)	Sediment POC	Benthic Bacteria	Sediment POC
Neuse Estuary (late summer 1998)	Sediment POC	Sediment Bacteria	Sediment POC
St. Marks Seagrass, site 3 (Jan.)	Sediment POC	Benthic Bacteria	Sediment POC
Bothnian Sea	Sedimentary Carbon	Pelagic Producers	Sedimentary Carbon
Bothnian Bay	Sedimentary Carbon	Pelagic Producers	Sedimentary Carbon

Table 61 Top ranked actors based on Control and Dependence Analysis for UIEs

Network		Control		Dependence
Central Arizona-Phoenix Nitrogen				
	1	Near-surface atmosphere	1	Pets
	2	Crops	2	Humans

	3	Subsurface	3	Subsurface
Central Arizona-Phoenix Nitrogen no Landfill				
	1	Near-surface atmosphere	1	Pets
	2	Crops	2	Humans
	3	Subsurface	3	Subsurface
Toronto Nitrogen 1990				
	1	Incineration	1	Human Bodies
	2	Atmospheric Release	2	Circular Outputs
	3	Sewage Effluent		
Toronto Nitrogen 2001				
	1	Atmospheric Release	1	Human Bodies
	2	Sewage Effluent	2	Circular Outputs
	3	Incineration		
Toronto Nitrogen 2004				
	1	Atmospheric Release	1	Human Bodies
	2	Sewage Effluent	2	Circular Outputs
	3	Landfill		
Swiss Lowlands Timber				
	1	Incineration and waste management	1	Forestry
	2	Consumption of paper products	2	Production and trade of timber products
	3	Consumption of timber products	3	Production and trade of paper products
Swiss Lowlands Timber Scenario 1				
	1	Incineration and waste management	1	Forestry
	2	Consumption of paper products	2	Production and trade of timber products
	3	Production and trade of paper products	3	Production and trade of paper products
Swiss Lowlands Timber Scenario 2				
	1	Incineration and waste management	1	Production and trade of timber products
	2	Production and trade of timber products	1	Consumption of timber products
	3	Consumption of timber products	2	Forestry
Central Arizona-Phoenix Wastewater Nitrogen				
	1	Groundwater	1	Wastewater treatment plants
	2	Biosolids	2	3 tied
	3	Irrigated crops		
Trinket Island Energy				

	1	Human Nutrition	1	Food Processing
	2	Human Labor	2	Solar Panels
	3	Light	3	2 tied
Xiamen Energy		Control		Dependence
	1	Industry	1	Electric
	2	Electric	2	Resident
	3	Resident	3	Petrifaction
Beijing Energy 1995				
	1	Energy Consumption sector	1	Energy Exploitation sector
	2	Energy Recovery sector	2	Energy Transformation sector
	3	Energy Transformation sector	3	Energy Consumption sector
Beijing Energy 2000				
	1	Energy Consumption sector	1	Energy Exploitation sector
	2	Energy Recovery sector	2	Energy Transformation sector
	3	Energy Transformation sector	3	Energy Recovery sector
Beijing Energy 2005				
	1	Energy Consumption sector	1	Energy Exploitation sector
	2	Energy Transformation sector	2	Energy Transformation sector
Beijing Energy 2007				
	1	Energy Consumption sector	1	Energy Exploitation sector
	2	Energy Transformation sector	2	Energy Recovery sector
	3	Energy Recovery sector	3	Energy Transformation sector
Beijing Emergy				
	1	Industrial Sector	1	Domestic Sector
	2	Domestic Sector	2	Agricultural Sector
	3	Agricultural Sector	3	Industrial Sector
Tianjin Emergy				
	1	Industrial Sector	1	Domestic Sector
	2	Agricultural Sector	2	Agricultural Sector
	3	Domestic Sector	3	Industrial Sector
Shanghai Emergy				
	1	Industrial Sector	1	Domestic Sector
	2	Agricultural Sector	2	Agricultural Sector
	3	Domestic Sector	3	Industrial Sector
Chongqing Emergy				
	1	Agricultural Sector	1	Domestic Sector

	2	Domestic Sector	2	Agricultural Sector
	3	Industrial Sector	3	Industrial Sector
Suzhou Material				
	1	Agriculture	1	Production and Supply of Water
	2	Other Manufacturing	2	Chemistry
	3	Services	3	Production and Supply of Electric and Heat Power
Vienna Carbon				
	1	Industry, trade, and service sector	1	Water and soil
	2	Domestic sector	2	Energy production sector
	3	Agriculture sector	3	Construction sector
Stockholm Nitrogen				
	1	Air	1	Food Supply
	2	Water	2	Service
	3	Waste Management	3	Real Estate
Stockholm Phosphorus				
	1	Waste Management	1	Food Supply
	2	Water	2	Real Estate
	3	Households	3	Service
Beijing Nitrogen 1996				
	1	Atmosphere	1	Industry
	2	Surface water	2	Crop Cultivation
	3	Forest	3	Pets
Beijing Nitrogen 2000				
	1	Atmosphere	1	Industry
	2	Surface water	2	Crop Cultivation
	3	Forest	3	Pets
Beijing Nitrogen 2004				
	1	Atmosphere	1	Industry
	2	Surface water	2	Crop Cultivation
	3	Forest	3	Pets
Beijing Nitrogen 2008				
	1	Atmosphere	1	Industry
	2	Surface water	2	Crop Cultivation
	3	Forest	3	Pets
Beijing Nitrogen 2012				
	1	Atmosphere	1	Industry
	2	Surface water	2	Crop Cultivation
	3	Forest	3	Farmland
Gavle Phosphorus				

	1	Waste Dumps	1	Poultry
	2	Population Centre	2	Forests and Agriculture
	3	Sewage Treatment Plant	3	Population Centre

Table 62 Top ranked actors based on Control and Dependence Analysis for Food Webs

Network		Control		Dependence
Bothnian Bay				
	1	Meiofauna	1	Dissolved Organic Matter
	2	Sedimentary Carbon	2	Pelagic Producers
	3	Macrofauna	3	Benthic Producers
Bothnian Sea				
	1	Macrofauna	1	Pelagic Producers
	2	Sedimentary Carbon	2	Benthic Producers
	3	Meiofauna	3	Dissolved Organic Matter
Georges Bank				
	1	Megabenthos- filterers	1	Phytoplankton- Primary
	2	Bacteria	2	Small Pelagics- squid
	3	Microzooplankton	3	Small copepods
Gulf of Maine				
	1	Macrobenthos- other	1	Phytoplankton- Primary
	2	Bacteria	2	Small Pelagics- other
	3	Microzooplankton	3	Small Pelagics- anadro
Lake Oneida (post-ZM)				
	1	Sedimented Detritus	1	Snails
	2	Freshwater Drum	2	Green Algae
	3	Smallmouth Bass	3	Euglena
Lake Oneida (pre-ZM)				
	1	Sedimented Detritus	1	Golden Algae
	2	Walleye Age 4+	2	Snails
	3	Freshwater Drum	3	Euglena
Bay of Quinte (post-ZM)				
	1	Sedimented Detritus	1	Diatoms
	2	Double Crested Cormoran	2	Flagellates
	3	Walleye Age 1-3	3	Leeches
Bay of Quinte (pre-ZM)				
	1	Sedimented Detritus	1	Green Algae
	2	Walleye Age 1-3	2	Flagellates

	3	Longnose Gar	3	Isopods
Middle Atlantic Bight				
	1	Macrobenthos- other	1	Phytoplankton- Primary
	2	Bacteria	2	Mesopelagics
	3	Microzooplankton	3	Small Pelagics- other
Southern New England Bight				
	1	Microzooplankton	1	Small Pelagics- other
	2	Bacteria	2	Phytoplankton- Primary
	3	Macrobenthos- other	3	Shrimp et al.
Sylt-Romo Bight				
	1	Sediment Particulate Organic Carbon	1	Phytoplankton
	2	Meiobenthos	2	Macrophytes
	3	Black-headed Gull	3	Carcinus maenas
Cypress (dry)				
	1	Vertebrate Detritus	1	Fish PC
	2	Living SED	2	Roots
	3	Refractory Detritus	3	Living Particulate Organic Carbon
Cypress (wet)				
	1	Vertebrate Detritus	1	Passeriformes onniv.
	2	Living SED	2	Fish PC
	3	Refractory Detritus	3	Roots
Florida Bay (dry)				
	1	Water Particulate Organic Carbon	1	Detritivorous Amphipods
	2	Benthic Particulate Organic Carbon	2	Herbivorous Amphipods
	3	Water Flagellates	3	Benthic Phytoplankton
Florida Bay (wet)				
	1	Water Particulate Organic Carbon	1	Benthic Phytoplankton
	2	Water Flagellates	2	Detritivorous Amphipods
	3	Benthic Particulate Organic Carbon	3	Benthic Crustaceans
Graminoids (dry)				
	1	Sediment Carbon	1	Mesoinverts
	2	Refractory Detritus	2	Other Macroinverts
	3	Otter	3	Large Aquatic Insects
Graminoids (wet)				
	1	Sediment Carbon	1	Mesoinverts
	2	Refractory Detritus	2	Other Macroinverts
	3	Snakes	3	Large Aquatic Insects
Mangroves (dry)				

	1	Bacterica Sediment	1	Insects
	2	Particulate Organic Carbon	2	Other Phytoplankton
	3	Carbon in Sediment	3	Larvae
Mangroves (wet)				
	1	Bacteria Sediment	1	Insects
	2	Particulate Organic Carbon	2	Amphipods
	3	Carbon in Sediment	3	Other Phytoplankton
Narragansett Bay				
	1	Detritus	1	Phytoplankton
	2	Hetero Microflag	2	Benthic Algae
	3	Sed Particulate Organic Carbon Bacteria	3	Mesozooplankton
Northern Benguela Upwelling				
	1	Particulate Organic Carbon	1	Phytoplankton
	2	Microplankton	2	Benthic Alage
	3	Seals	3	Mesozooplankton
Neuse Estuary (early summer 1997)				
	1	Sediment bacteria	1	Benthic microalgae
	2	Free living bacteria	2	Pelagic fish
	3	Sediment Particulate Organic Carbon	3	Suspended Particulate Organic Carbon
Neuse Estuary (early summer 1998)				
	1	Sediment bacteria	1	Benthic microalgae
	2	Sediment Particulate Organic Carbon	2	Pelagic fish
	3	Birds	3	Suspended Particulate Organic Carbon
Neuse Estuary (late summer 1997)				
	1	Sediment bacteria	1	Benthic microalgae
	2	Sediment Particulate Organic Carbon	2	Pelagic fish
	3	Free living bacteria	3	Suspended Particulate Organic Carbon
Neuse Estuary (late summer 1998)				
	1	Sediment bacteria	1	Benthic microalgae
	2	Sediment Particulate Organic Carbon	2	Pelagic fish
	3	Birds	3	Suspended Particulate Organic Carbon
St. Marks Seagrass, site 1 (Feb.)				
	1	Sediment Particulate Organic Carbon	1	micro-epiphytes
	2	benthic bacteria	2	zooplankton
	3	meiofauna	3	Halodule
St. Marks Seagrass, site 2 (Feb.)				
	1	Sediment Particulate Organic Carbon	1	Halodule
	2	benthic bacteria	2	micro-epiphytes
	3	meiofauna	3	phytoplankton

St. Marks Seagrass, site 4 (Feb.)				
	1	Sediment Particulate Organic Carbon	1	benthic algae
	2	benthic bacteria	2	micro-epiphytes
	3	suspended Particulate Organic Carbon	3	Halodule
St. Marks Seagrass, site 1 (Jan.)				
	1	Sediment Particulate Organic Carbon	1	zooplankton
	2	benthic bacteria	2	micro-epiphytes
	3	omnivorous crabs	3	sheepshead minnow
St. Marks Seagrass, site 2 (Jan.)				
	1	Sediment Particulate Organic Carbon	1	zooplankton
	2	benthic bacteria	2	phytoplankton
	3	red drum	3	sheepshead minnow
St. Marks Seagrass, site 3 (Jan.)				
	1	Sediment Particulate Organic Carbon	1	benthic bacteria
	2	suspended Particulate Organic Carbon	2	zooplankton
	3	predatory gastropod	3	benthic algae

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